A process-driven approach to the understanding of developmental differences in cognitive flexibility in young children and adults

A process-driven approach to the understanding of developmental differences in cognitive flexibility in young children and adults

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Declaration

I confirm that this thesis titled '*A process-driven approach to the understanding of developmental differences in cognitive flexibility in young children and adults'* is the outcome of the research undertaken by myself, and I am the sole author of the thesis. The content here has not been submitted for a degree to any other university or institute.

Anna Peng

Date:

Signature:

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Thesis Abstract

The ability to update one's goal in a changing environment and adapt actions accordingly is often thought to reflect cognitive flexibility. Early childhood, from 3 to 6 years of age, is witness to a large improvement in this ability. In real life, environmental changes can be incredibly dynamic and fast, thus flexible behaviours need to happen in a timely manner. Moreover, attention operates in a multisensory environment so switching between tasks is often carried out cross-modally (e.g. stop doing the colouring exercise and put the story books away when being told to). Developmental studies with young children have generally focused on specific aspects of how the switch is *initiated*, if at all, in a unimodal, highly controlled framework. This approach may miss out aspects of task switching important for understanding cognitive flexibility in a wider context that relates better to real-world dynamics. Thus, the current thesis investigates young children's task switching abilities in a temporally-driven and multisensory context.

My thesis combines two approaches: (1) behavioural experiments with children and adults, and (2) computational modelling. Three behavioural experiments were carried out with 4-year-olds, 6-year-olds and adults. These experiments were unimodal task-switching (UTS), cross-modal task-switching with bimodal stimuli (bimodal CMTS) and cross-modal task-switching with unimodal stimuli (unimodal CMTS) respectively. In the cross-modal experiments, not only did the participants have to switch between tasks, but the stimuli associated with the tasks could be either visual or auditory. Past research has suggested that young children can exhibit cross-modal attention effects different from those observed in adults (e.g. modality dominance).

However, it remains unclear how the developmental differences in cross-modal attention manifest in a highly task-oriented context. The task-switching procedures in these experiments draw heavily from established adult task-switching paradigms.

The computational models followed the principles of Interactive Activation as described in Gilbert and Shallice (2002). These are connectionist networks with units and connections between the units. The models were used to understand the behavioural results in the bimodal CMTS experiment. A series of computational models are used to understand what factors affect performance on different trial types, how task representations and responses can be triggered proactively and reactively, and how variations in performance can be modelled using a *population modelling* approach.

The thesis combines the current understanding of the development of cognitive control with the literature on information processes in task-switching. Finally, the thesis proposes answers to questions such as what behaviours/measures are reflective of the development of cognitive function or constraints, of information processes associated with specific tasks, and of the inter-individual differences present at different ages.

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Chapter 1. What can flexible behaviours tell us about the development of cognitive control?

It is now well established that cognitive control and brain development undergoes a protracted development from early years well into adulthood (Amso & Scerif, 2015; Best & Miller, 2010; Fair et al., 2009; Giedd et al., 1999; Johnson, 2001, 2011; Rice & Barone, 2000). Within this timescale, children from 3 to 6 years of age bear witness to dramatic improvements in their cognitive control, as they start to show the ability to adhere to instructions and regulate their behaviours appropriately. Indeed, the development of cognitive control during early childhood has been main focus of much developmental research (Bull, Espy, Wiebe, Sheffield, & Nelson, 2011; Carlson, 2005; Diamond, Carlson, & Beck, 2005; Gerstadt, Hong, & Diamond, 1994; Wiebe, Espy, & Charak, 2008; Zelazo, 2006). The development of cognitive control is perhaps best manifested in situations where cognitive flexibility is required. Although relatively poorly defined, cognitive flexibility broadly refers to the ability to update mindsets adaptively to the changing environment, often in the face of interference, and to carry out appropriate goal-directed actions (Freier, Cooper, & Mareschal, 2017). Many studies have documented a large improvement in cognitive flexibility during early childhood (e.g. Carlson, 2005; Cepeda, Kramer, & Gonzalez de Sather, 2001; Cragg & Nation, 2009; Zelazo, Müller, Frye, & Marcovitch, 2003).

One popular way to assess cognitive flexibility during early childhood is to study how children switch from one task to a different cognitive task (e.g., Fisher, 2011; Kirkham, Cruess, & Diamond, 2003; Kloo & Perner, 2005; Zelazo, 2006); although different in methodological detail, research on cognitive

flexibility in adults has also employed procedures that require switching between different cognitive tasks. Although both developmental studies and adult studies may at first appear similar in their common interest in cognitive flexibility, there are important differences in the experimental paradigms used with young children and those used with adults, making it difficult to map out the developmental changes in attention control across lifespan. Importantly, developmental research has generally focused on how children *initiate* a switch in behaviour, whereas adult studies have focused on how adults *manage* dynamic changes in the task environment.

Laboratory experiments with young children often utilise tasks similar to each other with a limited range of stimuli (the colour-shape tasks being the most common of all). Focusing on behaviours with a limited range of tasks may potentially underestimate young children's ability to change their goal-directed behaviours adaptively. In this thesis, I will argue that cognitive flexibility should be examined with different types of tasks, and in situations where environmental changes are frequent and fast. The logic is simple: if cognitive flexibility is a general skill associated with the child's overall development, then it should be examined with different types of tasks, different types of stimuli, different task instructions and different temporal dynamics. In addition to arguing for the importance of the diversity of task context, in this thesis, I will also argue that cognitive flexibility should be examined in a *multisensory environment*.

My research combines convergent approaches; namely, behavioural studies and computational models. While the behavioural findings from past and present studies have allowed me to theorise about how developmental differences in performance may occur, and what associated information processes may underlie the performance differences observed in children and

adults, computational models allow me to explicitly test the relevance of different parameters associated with the theories, and in the process, to generate new prediction relevant to behavioural experiments.

In this introduction, I will discuss the similarities and differences of the premises underlying theories of cognitive flexibility in children and adults, as well as in the paradigms used in either developmental and adult studies of cognitive flexibility, before suggesting that bridging between the two domains is necessary in order to appreciate the more nuanced aspects of the development of cognitive control. I will also discuss the importance of understanding cognitive flexibility in a multisensory setting, and of understanding different forms of attentional shifts—those occurring between tasks and those occurring between modalities. Finally, I will talk about the importance of grounding control mechanisms within contexts, and about the benefits of computational models for understanding developmental, task-specific, and modality-specific effects in cross-modal task-switching studies.

1.1 Are flexible behaviours underpinned by continuous development?

Three-year-olds often have difficulties in flexibly shifting between different mental representations, and this ability improves between 4 to 5 years of age (Carlson, 2005; Zelazo, 2006; Zelazo & Frye, 1998). In particular, younger children are more likely to exhibit perseverative behaviours, since they often appear to stick to the previous task rule even when the situation has changed. The observation of perseverative errors is often taken as evidence of poorer flexibility in young children. A canonical paradigm that investigates preschool children's cognitive flexibility is Dimensional Card Change Sorting

task (*DCCS*[1]), first proposed by Zelazo (Zelazo, 2006; Zelazo & Frye, 1998). The original task involves verbally asking children to sort a deck of cards that contain multidimensional information (e.g. '*red* truck' and '*blue* rabbit') with one dimension in the pre-switch phase (e.g. colour), and another dimension (e.g. shape) in the post-switch phase. While most children are able to sort the cards correctly in the pre-switch phase, three-year-olds have a substantial difficulty in sorting the cards correctly in the post-switch phase. In contrast, most 4-year-olds are able to sort the cards correctly in the post-switch phase.

The DCCS is challenging on many levels: from limited practice opportunities, lack of foreknowledge about the experimental procedure, counterintuitive task changes, reliance on verbal instruction, lack of feedbacks, to high level of interferences between task sets. Thus, subsequent studies that have attempted either to reduce the level of task set interferences or to encourage children to engage in the alternative dimension, have been largely successful in improving the pass rates in young children (Hanania, 2010; Kirkham, Cruess, & Diamond, 2003; Kloo & Perner, 2005). What remains unclear is which of these factors (that facilitate/hinder task performance) are directly related to cognitive flexibility.

Perhaps the most striking finding with the DCCS task is not so much the absolute level of performance of 3-year-olds, but the dissociation between the children's correct verbal response to task rules when being queried, and the incorrect sorting actions during the post-switch phase. Young children typically

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[1] Glossary of terminology throughout this thesis can be found in Appendix A

can recall the correct task rule when being verbally queried, and thus it is generally assumed that the children *know* what they are expected to do, but nonetheless *fail* to do so. The dissociation between thought and action is often taken as a lack of wilful control, and not a lack of awareness of the appropriate task rules. Equipped with this observation, researchers have generally explained the poor performance in young children by appealing to a unitary account such as an inhibitory deficit to direct attention away from an initial representation formed during the pre-switch phase (Kirkham & Diamond, 2003), an inability to construct task rules in a hierarchically complex manner (Zelazo & Frye, 1998), or an inability to actively maintain current goals or other weaknesses in representations (e.g. Chevalier & Blaye, 2008; Kharitonova & Munakata, 2011; Munakata, 2001).

Although the response to a verbal query and the sorting behaviour both appear to be associated with the same task context, and any adult may easily relate both to the same task context, the two events may not necessarily have the same meaning to children, and thus essentially constitute different tasks that required different cognitive operations (Munakata & Yerys, 2001). It is also possible that young children with limited verbal skills may not see the significance in translating the verbal instruction into a change in action, particularly when they are already motivated to do whatever they have been successfully doing so far (i.e. sorting cards by the first dimension).

Without ensuring that children of different ages have the same understanding of the task instructions and task demands (at least to some degree), it is difficult to know how cognitive flexibility develops. Many developmental studies appear to favour the pass/fail measure of cognitive flexibility with counterintuitive tasks similar to DCCS (e.g., the Day/Night task, in

which the participants have to say ‘Night’ or ‘Day’ when presented with a counterintuitive image of a sun or a moon respectively; see Carlson, 2005, for a complete review). Because these tasks all have pass/fail outcomes, they can lead to a relatively restricted all-or-none perception of cognitive flexibility. This restricted approach to the study of cognitive flexibility may be due in part to the fact that developmental studies are often motivated to find the largest measureable difference between age groups, at least at the beginning of the research. In addition to this latent motivation, with very young children, there is often a challenge in envisioning an age-appropriate yet suitably complex task that permits the investigation of cognitive flexibility. These factors often result in experimental paradigms that have a limited range of ages to which the paradigms are applicable, since children in one age group often perform poorly and the children in another age group are at ceiling levels of performance.

Dichotomous pass/fail measures may be useful to understand the *starting point* of flexible behaviour, but can be an insensitive measure of the *continuous development* of cognitive flexibility. Development occurs across time, with important sensitive periods and maturation timescales within and between different brain regions (Amso & Scerif, 2015; Giedd et al., 1999; Lenroot & Giedd, 2006; Paus et al., 1999). Interactions between the various processing pathways, with differing degrees of maturation, should give rise to subtle and continuous behavioural/physiological differences that are beyond what simple dichotomous measures can detect. By focusing only on what children can or cannot do, there is a danger of missing out on a great opportunity for understanding how development affects each stage of information processes, from goal setting, formulating internal models of task sets, encoding task-associated information, interference between task sets,

internal interference from attentional biases or inattentiveness, to planned and unplanned actions. Since posterior brain regions responsible for lower-level information processes and anterior frontal control centres are both under major architectural change across development, cognitive flexibility in children is likely to lie somewhere in between a domain-general and a task-specific ability (Deák & Wiseheart, 2015).

In sum, young children's ability to flexibly adapt their behaviours to environmental changes may have been underestimated by the existing studies that rely on dichotomous measures. If so, then a key question remains unanswered; namely, how do developmental changes in cognitive control relate to changes in generalizable and/or specific flexible behaviours? In the next section I will review some theoretical accounts of cognitive flexibility and what they mean to flexible behaviours when considering cognitive flexibility from an information-processing standpoint.

1.2 What abilities underlie cognitive flexibility?

Different developmental researchers view 'cognitive flexibility' differently. The definition of cognitive flexibility is elusive since different experiments focus on different aspects of the cognitive operations required for that specific task. That said, cognitive flexibility is likely to be greater than the sum of experimental findings! One example of the inconsistent views of cognitive flexibility is that cognitive flexibility is often defined conceptually in the introduction of a journal article, and then defined operationally in the discussion sections. At the conceptual level, cognitive flexibility is often defined as the ability to *simultaneously* hold goal representations online, resolve conflicting information, and shift attention and respond appropriately to environmental changes (e.g.

Davidson, Amso, Anderson, & Diamond, 2006; Diamond, Carlson, & Beck, 2005; Zelazo et al., 2003), thus encompassing multiple cognitive operations. However, the specificity of these core cognitive operations remain largely elusive (Cragg & Chevalier, 2012) .

In comparison, operationally, cognitive flexibility in developmental research is often defined with a specific theoretical account relevant for a specific experimental result only. The tendency to propose a restricted theoretical account for a complex behaviour reflects the methodological constraints of behavioural studies, since only a limited number of independent variables can be tested at one time in an experimental setting. Thus, it is not always clear how these precise theoretical accounts relate to the multi-faceted definition of cognitive flexibility at the conceptual level. Below I will give an overview of what some of the theoretical accounts are, and how it may be possible to approach cognitive flexibility more liberally, by moving beyond adopting a specific theoretical account of flexible behaviour.

(1) Cognitive flexibility may be about the ability to construct complex task rules. Zelazo's *Cognitive Complexity Control Theory* (Zelazo et al., 2003) posits that young children fail on the DCCS task because they are unable to form a complex, hierarchical 'if-if-then'-like rule structure. However, other studies that required a similar task structure have shown that 3-year-olds are able to switch their responses on tasks that require a similar hierarchical task rule, if the need to redescribe the same object is removed (Kloo & Perner, 2005; Perner & Lang, 2002). Kloo and Perner (2005) argued that young children may simply be unaware that one object can be two distinct things at the same time (e.g. a red object and a truck), and that this lack of awareness

prevents them from forming an appropriate task set. Crucially, whether an appropriate task representation is formed or not may not necessarily implicate the development of domain-general cognitive control, but may have more to do with learning about different possible concepts. If anything, DCCS tasks highlight the possibility that young children may form task representations differently from older participants under some situations, due to their limited experience with the task attributes and task structures.

(2) *Cognitive flexibility may be about the ability to actively maintain information*. Some authors have argued that a major source of performance error in children comes from their difficulty in actively maintaining the relevant goal state (Blaye & Chevalier, 2011; Chevalier & Blaye, 2008; Freier et al., 2017; Marcovitch, Boseovski, & Knapp, 2007). According to this view, external factors that assist children in maintaining goal states should facilitate performance. One way to facilitate goal representation is through transparent task cues, which has been shown to be particularly effective in improving performance in 4-year-olds (Blaye & Chevalier, 2011). Furthermore, it was found that young children sometimes fail to switch responses not necessarily because they perseverate with the previous task rule, but because they fail to activate the current task rule (Chevalier & Blaye, 2008; Marcovitch et al., 2007). Similarly focusing on representations, Munakata (Morton & Munakata, 2002; Munakata, 2001) argued that representations at different levels of processing are graded rather than all-or-none. When young children pass in one task but fail on another task that taps into the same kind of knowledge (e.g.

colour/shape), the underlying cause may be the difference in the requirement of how strongly these representations need to be activated to succeed on these two tasks. To support the graded representation account, Blackwell, Cepeda and Munakata (2009) found that 4- to 5-year-olds who were quicker in responding to simple no conflict task-rule queries were also better at switching between tasks with multivalent stimuli than those who were slow at answering simple questions. This was true even after controlling for simple processing speed, indicating that the ability to actively represent rule may underlie the differences between switcher and non-switchers.

(3) *Cognitive flexibility may be about the ability to resolve information interference*. Most developmental studies of cognitive flexibility involve task sets that have overlapping task attributes, either in the stimulus set, the response set, or both. Thus, one defining feature of cognitive flexibility, at least in the laboratory tests, is the ability to resolve interference.

Trial-to-trial and task-to-task interferences can exist at different levels of processing, and different ages may be more or less affected by the types of interference. Several studies have suggested that children aged between 5 and 7 years experienced a greater level of stimulus-based interference than older children and adults, but not necessarily response-based interferences (Cragg, 2016; Cragg & Nation, 2009). The general procedure in those studies involved independently varying the degree of dimensional overlaps among the stimuli (e.g. univalent colour-only stimulus vs. bivalent integrated coloured shape) for stimulus-based interference and varying how

many stimuli are mapped onto the same response for response-based interference. The interference in this context should be classed as *representational incongruency*, since the interference arises from how task sets were defined the first place. Thus, children's inflexible behaviours may be due to the lack of ability in overcoming representational interferences between stimulus attributes associated with the task goals.

(4) *Cognitive flexibility may be about inhibitory control on prepotent responses*. Children's difficulty with flexible behaviours may arise because they are unable to stop themselves from making a response, even when they know what the relevant task attribute is. In a series of spatial-compatibility studies using speeded tasks with children aged 4 to 13 years old and adults, Davidson et al. (2006) found that young children's performance was particularly affected by spatial incompatibility between the location of the stimulus and the response (this is also known as the Simon Effect), indicating difficulty in suppressing prepotent responses caused by spatial compatibility. In another study, Ling, Wong, & Diamond (2016) examined whether young children's difficulty in the Day/Night task (i.e. saying Day when seeing a picture of a moon) was due to response prepotency or weak task representation. They found that if there was an imposed delay between the stimulus and the response stages, such as the use of task-unassociated 'ditty song', children's performance on Day/Night task improved. This result suggests that young children may have a particular difficulty in inhibiting a prepotent response, particularly if the response can be strongly triggered by external cues, and that the

ability to inhibit a response appears to be independent to the control component of task representation (e.g. Diamond & Kirkham, 2005). Although inhibition of a prepotent response may be important in some situations, not all tasks necessarily elicit strong habitual responses. Thus, it is unclear what role inhibitory control plays in tasks where responses are less habitual in nature.

(5) *Cognitive flexibility may be about the ability to update task approaches and monitor performance adaptively*. This ability cannot be measured at a single specific time point in the task, such as the point of switch, but rather, should be examined through the *continuous changes* in behaviours. In this view, flexibility is defined as the ability to take in new information and dynamically revise task approaches (i.e. plans and actions). This means that even when the behaviour initially appears inflexible, through continuous revision of internal representations and planned actions, adaptive flexible behaviours can emerge later on. There are reasons to believe that young children's ability to change their behaviour within a task context may be better than what the standard laboratory tests suggest. For example, Kloo and Perner (2003) found that false-belief training improved performance on the DCCS task, and that DCCS training also improved performance on false-belief tasks in 3- and 4-year-olds. Both false belief and DCCS tasks required the participants to view the same object from an alternative perspective. Their result shows that once children are encouraged to view the same object differently in the first task, they are able to apply a similar approach to a different task. Importantly, this training effect is not to do with the development

of control itself, but to do with the understanding and exploration of different approaches in a given task context.

In all likelihood cognitive flexibility is closely associated with most if not all of the above abilities, and modulated by task-specific demands and structural variables such as cueing, feedback, probabilities of switches, task attributes, task conflicts, and so on. Although the picture outlined here may seem overwhelmingly complex, when broken down, each ability may only matter to different stages or aspects of information processing. For example, to undertake a task, one must form a task representation within a specific context, and exhibit the ability to form an appropriate rule structure (Point 1). The person then needs to employ some form of control to maintain this task representation throughout the duration of the trial (Point 2). To be able to carry out actions purposefully, one must be able to select what information is relevant to the current goal, and filter out the irrelevant and interfering information (Point 3). Once a change of goal is recognised, the person must be able to adjust their response plan according to the new task rule. This new response plan may only be weakly represented in the face of strongly triggered habitual response. Thus, the person needs to overcome the urge to respond too quickly through mechanisms such as inhibitory control (Point 4). And finally, the person may monitor their current state in the overall task context and form an internal representation of the task events, and consciously or unconsciously update task strategies that alter the performance in future tasks (Point 5).

When multiple information processes are in operation, and when each process is dependent on different abilities and experimental factors, any observed behaviour may not be easily attributable to a single cause. For

example, any developmental differences in active task representation may be masked by the response prepotency if the context strongly triggers a habitual response. Similarly, any developmental difference in conflict resolution may be masked by the differences in structural representations of the task set (i.e. when the participant failed to know what the current task goal is). Thus, our understanding of cognitive flexibility may need to move beyond a single factor, and importantly, beyond the sole measure of accuracy. Thus, in this thesis, I will argue that cognitive flexibility may be better investigated by placing greater emphasis on understanding the information processes that take place within the task context, within an individual, and within the developmental constraints (for a similar perspective, see Deák & Wiseheart, 2015).

In the next section I will be describing task-switching studies of adults that focus on the information processing underlying flexible rule switches, and look for both conceptual and procedural overlaps between adult and developmental studies of cognitive flexibility. These overlaps will provide the framework for how cognitive flexibility is viewed and investigated in the current thesis.

1.3 The adult task-switching paradigm

Task-switching is a canonical paradigm for investigating the control processes in flexible goal-oriented behaviours in adults (see Monsell, 2003). In this paradigm, participants are required to switch between two—or sometimes three—different tasks. However, unlike in the developmental studies where tasks often switch only once or at most a few times, the adult task-switching paradigm involves frequent alternations between different task sets (e.g. AA**B**B**A**A…, where bold letters are task-switch trials). In addition, adult task-

switching studies have focused on RT changes as high accuracy is a desirable criterion within the studies. The experiments have often involved a practice part to ensure that the participants are familiar enough with the stimuli and the associated task rules (e.g. (Allport & Wylie, 2000; Rogers & Monsell, 1995; Rubinstein, Meyer, & Evans, 2001). Therefore, the main research interest in adult studies lies within the cognitive processes that underlie *multi-tasking* (within a context but not at the same time) and *task-switching*, within the existing cognitive control systems. Both control mechanisms and information processes within the task have been subjected to intense scrutiny (for a comprehensive review, see Kiesel et al., 2010). A *task set* in a task-switching experiment is generally defined with multiple components—a task goal (e.g. colour task), a task cue, and a set of governing rules relevant to the task goal (e.g. stimulus-response mappings). The studies using this task-switching procedure generally measure the performance differences between task-repetition trials and task-switch trials within the same task context. Reaction times and to a lesser degree, errors, are larger on the switch trials than on repetition trials. This cost is termed local *switch cost*, since it represents transient differences between the successive trials.

The task-switching paradigm also allows for the comparison between different task contexts—such as a pure 'single-task' block, and a mixed 'multi-task' block. The mixed task block involves both task-repetition and task-switch trials, as previously described; in contrast, the pure task block involves only one task, thus no rule switch is involved. The comparison between the pure task and mixed task block yields another type of performance cost—global *mixing cost*—manifested by a longer RT and lower accuracy on the repetition trials in the

mixed task block, than on trials in the pure block, despite the absence of rule change on either trial types.

These two most-investigated between-condition costs are discussed below with their respective plausible mechanisms.

1.3.1 Between-condition effects

RT switch cost is often seen as the time needed for the additional cognitive operations in task reconfiguration on switch trials, compared to repetition trials, and is thought to implicate cognitive controls (Rogers & Monsell, 1995). Support for the need of endogenous control in switching task comes from studies that modulate the effectiveness of task preparation, such as preparation window (e.g. Rogers & Monsell, 1995), anticipation of task changes (Monsell & Mizon, 2006), and task cue transparency (Koch, 2003; Logan & Bundesen, 2003; Logan & Schneider, 2006b). While many agree that switching to an alternative task requires endogenous control, it is still unclear whether switching to another task requires *additional* cognitive control processes, compared to repetition trials.

A *task set* generally consists of a task representation that refers to a goal or an intent (e.g. colour task), and the constituents that make up the task rules to achieve the goal (e.g. stimulus-response associations). Since a task set is composed of multiple components, task preparation is also theorised to be a multi-stage operation. It is generally thought that the first stage involves updating the goal representation and the second stage involves retrieval of the associated task rules (Mayr & Kliegl, 2000; Monsell & Driver, 2000; Rubinstein et al., 2001). While the first stage of intentional update is carried out during the preparation window, the second stage of preparation may be completed

exogenously only upon seeing the stimulus, which prompts the retrieval of specific S-R mappings.

Although switching tasks is likely to implicate cognitive control, it is generally agreed that there are multiple components contributing to the overall switch cost, some of which are more of a by-product of the information processes, such as information interference, rather than cognitive control itself. In task-switching studies, representational overlaps are often inherent in the stimulus and response sets. Thus when the task changes, there can be lingering interference from the previous trial(s) (Allport, Styles, & Hsieh, 1994; Wylie & Allport, 2000). This interference, collectively causes *task set inertia*, and is thought to be made up of both positive priming interference of the just-executed S-R event, negative priming of the ignored stimulus, as well as the lingering inhibition of the previously inhibited task set.

RT Mixing cost was originally thought to reflect the greater working memory demand (WM) in the mixed task block, compared to the pure task block (Los, 1996). However, later studies showed that increasing the number of task rules did not affect the size of mixing cost. Instead, mixing cost may reflect inherent ambiguity about the mixed task elements (Rubin & Meiran, 2005), which may require multiple steps of selection to resolve the information ambiguity (Steinhauser & Hübner, 2005).

If the difference between pure and mixed task blocks is the requirement for selection processes in the latter condition, then distinct cognitive operations may be found in the mixed block as compared to the pure block. Indeed, an electroencephalography (EEG) study has shown differential topography in the early ERP (event-related potential) components on pure trials, compared to trials in the mixed block; in contrast, switch and repetition trials in the mixed

block showed a similar topography and ERP components (Tarantino, Mazzonetto, & Vallesi, 2016; Wylie, Murray, Javitt, & Foxe, 2009). It thus suggests that different cognitive processes may be at play between the pure and mixed task blocks, perhaps more so than between the switch and repetition trials.

Other than the between-condition switch and mixing costs, which are sensitive to different trial types, RTs on the same trial type can also change from moment to moment as a function of within-condition effect.

1.3.2 Within-condition effects

Although between-condition switch and mixing costs are reliably observed in most studies, RTs often fluctuate across a sequence of trials. Such effects are referred to as *within-condition effects*. For example, De Jong (2000) observed that on the fastest switch trials, RTs were comparable to those on repetition trials. This result indicates that switch costs are not a universal phenomenon, and can vary within the task context itself. He argued that successful full task preparation on switch trials can happen, but only occasionally; on some trials, the task reconfiguration process is not complete and can continue after the stimulus onset. This within-condition performance variation is likely to reflect how participants approached the task—since task-switching experiments require participants to sustain attention for a long time, participants are likely to deploy control sufficiently but conservatively, due to the taxing nature of a continuous cognitive control. As a result, on some switch trials, the participants only reactively complete task reconfiguration upon seeing the stimulus (such as the retrieval of S-R rule). Support for the all-or-none preparation has also come from neuroimaging study. Wylie, Javitt and Foxe

(2006) found that if the participants can activate the neural circuit associated with the task prior to the stimulus onset, no switch cost was observed. A similar finding of a greater activation on successful switch trials (i.e. no switch cost) was also reported by Braver, Reynolds and Donaldson (2003).

Indeed, several studies argue for a strategy-dependent perspective on task preparation (Brass & von Cramon, 2004; De Baene & Brass, 2014; Forrest, Monsell, & McLaren, 2014; Forrest, Elchlepp, Monsell, & McLaren, 2012; Poljac & Yeung, 2014; Wylie et al., 2006). Task-strategy is likely to be modulated by how the task context is interpreted, and is sensitive to factors that motivate a specific approach, construct the task structures, and thus affect how information conflicts are played out within the system. De Baene and Brass (2014) have argued that the differences observed between repetition and switch trials are not necessarily driven by different underlying cognitive processes, but rather by the contextual factors that affect the preparatory strategies used on these trial types. Thus, performance differences observed in switch and mixing trials can be by-products of the underlying task strategies used on these trials, rather than the result of inherent differences in cognitive control processes operating between trial types.

In sum, adult task switching studies have identified two key types of costs: between-condition costs further broken down as either switch costs or mixing costs, and within-condition costs related to strategy selection.

1.4 Does the same measure of cognitive flexibility mean the same thing in different age group?

Although developmental and adult studies are motivated by a common interest, it is not clear if the different experimental paradigms used with these

two populations measure the same cognitive processes. Cragg and Chevalier (2012) provides an excellent review of the differences and similarities between the paradigms commonly used with young children and adults. These include differences in task instruction, types of stimulus and response sets, as well as differences in dependent measures. As discussed previously, the developmental studies on switching ability have placed a lot of emphasis on the *functional* accounts of inflexible behaviour (e.g. goal representation, inhibitory control, cognitive complexity etc.). In contrast, adult studies have focused on the information processes involved in the trial-to-trial changes occurring within the overall experimental context.

Although the ways that developmental and adult research have approached the question of cognitive flexibility differ slightly, there may be enough common ground to bridge between the two disciplines. In this section, I will therefore discuss some common factors that affect performance in both adults and children.

1.4.1 Common processes in switching tasks in children and adults

1.4.1.1 Retrieval process

The ease of memory retrieval affects switching performance in children and adults alike. Since the demand for memory retrieval is the highest on switch trials, the magnitude of a switch cost is directly affected by the memory retrieval process. Adult studies have suggested that task reconfiguration on switch trials can be a two-stage process— the first stage involves updating the current goal (intention), and second stage involves the retrieval of task rules (Mayr & Kliegl, 2000; Monsell & Driver, 2000; Rubinstein et al., 2001). Difficulties in either stage may affect the size of any observed switch cost. For example, the first stage of

preparation may be affected by how easily the task cue can be translated into a goal representation. Past studies suggest that both children and adults are affected by cue transparency. Young children performed better on a colour-shape task with transparent cues, than with arbitrary task cues (Chevalier & Blaye, 2009). Adults have also been found to be affected by cue retrieval difficulties (Logan & Schneider, 2006b, 2006a).

1.4.1.2 Carry-over interference and inhibition

Task-switching studies have generally involved task set overlaps that result in interferences. Moreover, switching back and forth between competing tasks requires reactivation and deactivation of task-relevant and irrelevant processes. On switch trials, the need for reactivation/deactivation is often the greatest since the processes relevant to the pre-switch trial becomes task-irrelevant and thus interfering. The collective interference from the previous task-irrelevant trial(s) forms a *task set inertia*, which is believed to contribute to performance cost on switch trials in both adults and children (Allport et al., 1994; Kirkham & Diamond, 2003). Task set inertia is likely to consist of multiple processes, including active concurrent interference such as the excitatory priming cost from the competing episodic events (FitzGibbon, Cragg, & Carroll, 2014; Waszak, Hommel, & Allport, 2003; Wylie & Allport, 2000), negative priming of the previously ignored stimulus attribute (Allport & Wylie, 2000; Müller, Gela, Dick, Overton, & Zelazo, 2006), and lingering activation of the irrelevant task goal and/or the persisting inhibition of the relevant task goal on switch trial (Allport et al., 1994; Mayr & Keele, 2000; Waszak et al., 2003).

Support for the idea of an excitatory *priming cost* comes from the observation that responses are slowed if the response on a switch trial is the

same as the previous trial (Rogers & Monsell, 1995). Interestingly when task-, cue-, stimulus- and response-repetition were manipulated independently, a substantial amount of RT change could be accounted for by the different forms of primes among the task elements, irrespective to the change of goal (Schmidt & Liefooghe, 2016). Thus, any change in the *priming compound* can contribute to RT costs. Switch costs may therefore reflect an overall net facilitative and interfering effect on a specific trial, and the size of which depends on task-specific context.

In contrast to the costs caused by the active interferences, slowed RT and errors can also be caused by persisting inhibition of the task-relevant processes. The persisting inhibition may happen at the perceptual level, resulting in negative priming. This *negative priming* effect refers to the performance cost in responding to a target that was previously ignored (e.g. inhibited) through selection processes (Neill, 1997; Steven P. Tipper, 1985, 2001). Inhibition can also be observed at a higher level of task set. By alternating between three tasks (A, B, C), Mayr and Keele (2000) found that switch costs were larger if the task was previously switched away from (e.g. ABA) than if it was not recently encountered (e.g. CBA). This effect was termed *n-2 repetition cost* (or backward inhibition) and is interpreted as evidence that on switch trials, the previous task was actively inhibited to avoid the danger of perseverative behaviours (Koch, Gade, Schuch, & Philipp, 2010; Mayr & Kliegl, 2000). Although n-2 repetition cost appears similar to negative priming, n-2 repetition cost may be more associated with endogenous control than is negative priming, since the cost is only observed on tasks with overlapping task interferences, but not on tasks without conflicts (for a review, see Koch, Gade, Schuch, & Philipp, 2010). In comparison, costs from negative priming occurs

more readily as long as the negatively primed information is filtered out during a previous selection process.

That said, the cost phenomenon can often be explained without a need to resort to inhibitory control. At least one study has, rather counterintuitively, found a larger negative priming effect in younger children than older children (Müller et al., 2006). If the size of negative priming indexes inhibition through control mechanisms, older children would be expected to be more affected by a negatively primed stimulus than younger children. As the results did not suggest that this was the case, it is possible that negative priming is an instrumental mechanism for stimulus selection, but that it does not relate directly to the control mechanism. Indeed, adult studies suggest negative priming can happen without resorting to an inhibitory control account, and can be explained by other non-inhibitory non-control processes (e.g.,Tipper, 2001).

Although the abovementioned inhibition phenomena, commonly measured in RT cost, may not necessarily be associated with inhibitory control, the ability to suppress a prepotent response does appear to share a common control mechanism across different tasks (Friedman & Miyake, 2004). Thus, it remains possible that young children's poorer performance in switching to an alternative task lies in their inability to suppress a prepotent response. However, this leaves open the questions of how prepotent the stimulus-response should be to warrant inhibitory control, and of how response prepotency is formed in task-switching studies with frequent S-R changes. Indeed, Friedman & Miyake (2004) have cautioned that inhibitory control mechanisms may be overextended as a causal mechanism in the literature on inhibition-related phenomena, and that there are likely to be many forms of inhibitory mechanisms, both controlled

or not controlled. Thus, researchers should be mindful when explaining performance costs with a singular inhibitory control account.

In sum, although active priming costs and persisting inhibition are likely to contribute to switch costs, the questions of whether inhibitory control is needed to account for the developmental differences in switching performance, and whether inhibition itself is associated with endogenous control, remain unanswered.

1.4.1.3 Sustained and adaptive control

Several researchers have proposed a dual-mechanism account for stable and adaptive cognitive controls. *Stable control* refers to the activation of the neural network that is sustained throughout a series of trials, within a larger task context. In contrast, *adaptive control* refers to the transient elevated activation of the neural network in response to a demand for information update. Both resting state and functional MRI support the dual-mechanism account of sustained and adaptive controls (Braver et al., 2003; Dosenbach et al., 2007). Demand for sustained control is greater in the mixed block since there is a need to maintain multiple intermixed information online. In contrast, demand for transient control is greater on switch trials since the task set requires reconfiguration.

The dual-mechanism account of task control also marries well with the concept of proactive and reactive controls in developmental studies (Chevalier et al., 2015; Doebel et al., 2017). *Proactive control* refers to a sustained cognitive control in anticipation of the need for a response, whereas *reactive control* refers to a temporary control in response to a change in the environment. The dual-control account also shares some similarities with other

hierarchical accounts of cognitive control, since sustained proactive control implies a need to bridge distinct temporal events through longer lasting stable controls. Notable examples of hierarchical control models include Koechlin and Summerfield's Cascade Model (2007) and Norman and Shallice's Supervisory Attention System (Norman & Shallice, 1986; Shallice, Burgess, & Robertson, 1996). Although these models vary in the degree of specificity of the temporal and functional organisations of their putative hierarchical controls, and of the specificity of cortical organisations of these controls, these models are both framed around the idea that higher-order sustained control can bias a lower-level decision-making process. Thus, in task-switching studies, transient control on switch trials is likely to be only part of the story of cognitive control that occurs during an extended sequence of behaviours. It is therefore possible that young children are equipped with the cognitive control to switch tasks, but still lack the ability to sustain this control throughout an extended sequence of trials.

1.4.2 What measures show developmental change?

Although both children and adults may engage in common information processes in switching between tasks, it is not clear what measures and what measurement methods reflect developmental changes best. The common measures used in task-switching studies are between-condition mixing cost and switch costs in RT and accuracy, as well as overall RT and accuracy on different trial types (pure trials in single-task block, repetition and switch trials in mixed-task block). In what follows, I will discuss these measures in the few developmental studies that have employed procedures similar to those in the adult task-switching studies.

1.4.2.1 Mixing cost

Several developmental studies that have employed a block design with pure- and mixed-task blocks have found developmental effects on mixing cost. For example, Davidson et al. (2006) carried out a series of experiments, involving task-switching elements, with children aged between 4 and 13 years of age, as well as on adults. The tasks involved response conflicts with spatial incompatibility. These required the participants to switch between responding on either the same or the opposite side of the screen to where the target stimulus appeared, based on the form of the stimulus. The authors reported greater global mixing costs in accuracy for children aged 10 years or younger, than for older participants. However, the accuracy mixing costs appeared as the result of a trade-off with RTs, with older participants showing greater RT mixing costs than younger children. Although accuracy mixing costs were greater with younger participants, this trade-off effect renders the overall effect of age on mixing costs difficult to interpret.

In another study with young children, Dibbets and Jolles (2006) carefully designed tasks suitable for preschool children (i.e. tasks on which young children had high accuracy). They also reported greater accuracy mixing costs among the youngest participants (aged from 4.8 years to 13 years of age), but no greater RT mixing costs. Thus, there was no change in the cost criteria between age groups (i.e., no speed-accuracy trade-off). However, some other studies have found an age effect on RT and/or accuracy mixing costs (Cepeda et al., 2001, with participants aged 7 to 82 years of age; Kray, Eber, & Karbach, 2008, with participants aged 7 to 77 years of age; Reimers & Maylor, 2005, with participants aged 10 to 66 years of age). Of course, these latter studies involved children older than the preschool years. Overall, past research generally

supports the presence of an age effect on mixing costs, although the types of costs (i.e. RT or accuracy) are less consistent across studies. Finally, at least one experiment has failed to find any influence of age on mixing costs using a colour/shape choice task, despite a large age gap in participants (7-year-olds vs. University students [Exp. 1], Ellefson, Shapiro, & Chater, 2006). Thus, this raises the question of whether the effect age on mixing costs is robust across different types of tasks.

1.4.2.2 Switch cost

Switch costs were found to interact with age in some studies (Cepeda et al., 2001, [7 to 82 years old]; Chevalier, Martis, Curran, & Munakata, 2015, [5 and 10 years old]; Crone, Bunge, Van Der Molen, & Ridderinkhof, 2006, [7 to 25 years old]; Davidson et al., 2006, [4 to 13 years old and adults]). However, numerous other studies have found no age effect on either RT or accuracy switch costs (e.g. Dibbets & Jolles, 2006, [4.8 to 13 years old]; Ellefson et al., 2006, [7 years old and adults]; Reimers & Maylor, 2005 [10 to 66 years old]). If switch cost is an effective measure of cognitive control in task set reconfiguration, and/or goal maintenance, developmental differences in switch costs should be observed. However, as discussed previously, switch costs can also be the result of task set inertia, which may or may not be resolved with control mechanism such as inhibitory control. If inhibitory control is needed to resolve effects of task set inertia, then younger children may exhibit greater switch costs than older participants. However, if task set inertia is just the result of the information processes, irrespective of age, then switch cost may not exhibit reliable interaction with age. Thus, at the moment it remains unclear whether switch costs are a meaningful correlate of cognitive development.

1.4.2.3 Processing speed

Many developmental studies suggest that processing speed changes as a function of global development, and is often seen as a mental resource that mediates other general ability such as IQ and fluid intelligence (Robert Kail, 2000; Park, Mainela-arnold, & Miller, 2015). This global account of processing speed comes from the observation that reaction time variability across different tasks can be mostly captured by simple linear regressions (Hale, 1990; Robert Kail, 2000; Kiselev, Espy, & Sheffield, 2009; Miller & Vernon, 1997). However, while much of the developmental difference in speeded tasks may be accounted for by processing speed alone, merely looking at processing speed in isolation may run the risk of overlooking other potentially age-dependent, function-specific and task-specific processes in complex speeded tasks. The issue of how changes in function-specific and task-specific processes may interact with the global development indexed by processing speed is particularly pertinent when it comes to young children between 3 to 6 years of age, since a slight change in task parameter can often have a dramatic impact on task performance (Huizinga, Dolan, & van der Molen, 2006). It is not clear, for example, if components in the task set inertia (e.g. priming cost) are more or less easily overcome because of differences in global processing speed, or because of some other specific functional processes such as working memory and inhibitory control.

1.4.2.4 Errors

Developmental studies of cognitive flexibility have shown that different types of errors decrease with age—perseverative errors or errors caused by difficulty in shifting goals (Crone, Ridderinkhof, Worm, Somsen, & van der Molen, 2004; Zelazo, 2006), distraction errors caused by weak goal

maintenance (Carroll, Blakey, & FitzGibbon, 2016; Chevalier & Blaye, 2008; Crone et al., 2004), and errors caused by prepotent motoric responses (Ling, Wong, & Diamond, 2016; Wright & Diamond, 2014). Although all error types decrease as a function of age, different error types may have different developmental trajectories. Crone and colleagues (2004) looked into this issue with participants from 8 to 25 years of age, on a task structurally similar to Wisconsin Card Sorting Task (WCST), and using a task-switching paradigm where the participants had to change rule through induction with error feedback or with explicit cues. They measured perseverative error on the trials immediately after the error feedback, and the distraction error on trials where the sorting behaviour changed from the chosen rule on the previous trial (i.e. without error feedback or being instructed so). The found that adult-levels of perseverative error were reached earlier in development than adult-levels of distraction error (Crone et al., 2004). This result was interpreted as evidence of an earlier maturation of the ability to shift goals than the ability to actively maintain task set.

Since the age group of interest in the current thesis is much younger than in Crone et al.'s study, it is likely that the errors committed by young children would encompass all error types. Thus, in the current thesis, instead of differentiating error types, accuracy serves only as an indicator of the overall level of development than to the development of a specific cognitive function. To achieve an overview of development by accuracy measure, it is important to have an experimental design that mitigates biases for a specific error type. Perseverative error happens only when the pre-switch rule can also be applied to the post-switch stimulus, such as when the stimulus is bivalent. In comparison, distractor errors may happen more sporadically, although they may

still be tied to the goal representations (Blakey & Carroll, 2018). It is possible that by intermixing bivalent, univalent and neutral stimuli in a task set, biases towards a specific error type can be minimised.

1.5 Flexible goal-directed behaviours in a multisensory environment

So far I have talked extensively about how cognitive flexibility was explored in both children and adults, in experiments based on *unisensory* tasks. There has been little discussion of how cognitive flexibility may operate in a multisensory context. However, we clearly live in a multisensory world. Thus, a key aim of the current thesis is to explore the development of task-switching within a multisensory environment, so as to better reflect this real-world context. In the real world one needs to not only be able to switch between tasks, but also between tasks in different sensory modalities. For example, young children need to learn to look out for cars when crossing the road, even when they are currently engaged in a conversation with their classmates. They need to use their multisensory attention system not only to *look* for cars, but also to *hear* the cars' approaching sounds, whist monitoring the social interactions.

We already know that the development of cognitive and attentional control is long and protracted (Best & Miller, 2010). In comparison, perceptual and multisensory systems show rapid progression in both differentiation and emergent interactions by the age of 2 (Bremner, Lewkowicz, & Spence, 2012; Lewkowicz & Ghazanfar, 2009). Although the multisensory system is already in place at an early age, children still exhibit many subtle differences in how they respond to multisensory information as compared to adults, such as the differences observed in modality dominance (Nava & Pavani, 2013; Robinson &

Sloutsky, 2010; Sloutsky & Napolitano, 2003), multisensory integration (Brandwein et al., 2011; Nardini, Bales, & Mareschal, 2016), cross-modal interference (Downing, Barutchu, & Crewther, 2015; Matusz et al., 2015; R. L. Thomas, Nardini, & Mareschal, 2017) and multisensory learning (Broadbent, White, Mareschal, & Kirkham, 2017). It is possible that the development that underpins cognitive and attentional control, also underpins the development of multisensory attention, given that attentional control may have a direct effect on how cross-modal information is processed (see Talsma, Senkowski, Soto-Faraco, & Woldorff, 2010).

Cross-modal attention is often explored in the context of interferences from concurrent cross-modal events. It has been well documented that adults' attention is often biased towards visual inputs rather than auditory inputs when encountering an audiovisual event. This attentional bias is termed *visual dominance* (for review, see Koppen & Spence, 2007). One example of adult visual dominance is the Colavita visual dominance effect, which is an overshadowing effect from visual input over auditory inputs. When presented with a quick audiovisual input, adults often only perceive the visual element of the audiovisual input (Colavita, 1974). In contrast to the visual dominance in adults, infants and young children's multisensory attention is dominated by auditory processing, exhibiting an auditory Colavita dominance effect (Nava & Pavani, 2013; Wille & Ebersbach, 2016). However, children's auditory dominance appears to extend beyond a simple overshadowing effect as they often make auditory-based judgements in learning-based tasks even when they have plenty of opportunities to process both auditory and visual inputs (e.g. Leary & Sloutsky, 2013; Robinson & Sloutsky, 2010; Sloutsky & Fisher, 2003).

Studies that investigate modality dominance have generally involved passive encoding of the stimulus, and do not impose high demands on cognitive control. Thus, it remains unclear if modality dominance affects performance when the behaviour is directed by an abstract task goal, as is the case in most task-switching studies. To date, there are no developmental task-switching studies that also include cross-modal attentional shifts.

In adult studies, shifting attention to another modality produces a reliable modality shift effect (MSE) in RT (Cohen & Rist, 1992). However, it is not clear if shifting between modalities is associated with endogenous control similar to that which occurs during task-switching. Lukas, Philipp and Koch (2010) found that if cues for the upcoming modality are provided, the MSE can be reduced through endogenous control. This effect may be synonymous to the preparation effect in task-switching studies (already discussed above). Thus, it may be possible that shifting between modalities and tasks taps into a common attentional control system, at least when cues are provided. Lukas et al. (2010) also observed an *asymmetry in the MSE*—RT costs were greater when shifting from visual to auditory than from auditory to visual modalities. It is unclear whether the smaller MSE when switching to visual targets is associated with visual dominance, or if it is a result of different levels of endogenous control on the visual and auditory trials, similar to the asymmetry cost reported between tasks that differ in difficulties (Gilbert & Shallice, 2002).

There have been only a handful of cross-modal task-switching studies with adults in which both visual and auditory stimuli shared the same task attribute as in unimodal task-switching studies (e.g., Hunt & Kingstone, 2004; Murray, Santis, Thut, & Wylie, 2009; Sandhu & Dyson, 2013). These studies explored the idea that, if the same endogenous system mediates switching

between tasks and shifting between modalities, then there may be an attentional bottleneck when both tasks and modality changed. An attentional bottleneck account would produce the largest RT cost when both modality and task changed, compared to either modality or task changing alone. So far, the evidence for a unitary attentional control system in cross-modal task-switching is mixed. Although RT costs can be largest when both task and modality are changed, adult cross-modal task-switching studies often report a less-than-expected cost that is subadditive to the combined modality shift cost and task switch cost (Hunt & Kingstone, 2004; Sandhu & Dyson, 2013; although see Murray et al., 2009 for comparison). The lack of conclusive evidence one way or another, suggests that cross-modal information processes are more complex than suggested by a simple dichotomy—modality-specific and task-specific processes are likely to operate both in parallel and interactively.

Since young children often exhibit different cross-modal attentional effects than adults, such as a different modality dominance, they may also exhibit cross-modal task-switching effects that differ from those of adults. While there is no direct developmental research on cross-modal task-switching, children and adults show differences in brain activation patterns in cross-modal oddball detection (Johannsen & Röder, 2014). If efficient cross-modal task-switches depend on the segregation of information or neural pathways to minimize interference, then young children may experience a greater cross-modal interference when switching between tasks due to lesser specialized networks (Fair et al., 2007a, 2007b). If so, children may need to exert a greater level of top-down control to overcome the interference at the lower processing level, and experience a greater attentional bottleneck in conditions in which cross-modal attentional shifting is required, compared to task-switching alone.

Thus, by combining the need to shift attention cross-modally and to switch attention between tasks, the current thesis sets the stage to explore how multisensory attention is deployed in a task-oriented context, and is well positioned to understand whether cross-modal attentional shift indeed interact with higher level cognitive/attentional control from a developmental perspective.

In addition to taking a behavioural approach to studying cognitive flexibility with *task-switching* and *modality-shifting*, the current thesis also employs computational modelling in an attempt to understand developmental differences in information processes associated the observe behaviours. In the next section, I will argue for the benefits of computational approach to developmental research. This will be followed by a brief overview of past computational models on task-switching.

1.6 Bridging the gap: why use computational modelling?

Findings in developmental cognitive psychology with young children have traditionally relied on descriptive theories to explain the observed behaviours that are lacking in mechanistic details (Mareschal & Thomas, 2006). For example, young children are said to have weaker representations of task goal, but questions such as how much weaker and why they are weaker, remain enigmatic with descriptive theories (e.g. is it due to inadequately activating the task goal in the first place; subsequent decay of the task goal once the environmental cue disappears; competition from the alternative task goals; and/or other forms of interferences and that interact with goal representations?).

Although descriptive theories are also used in adult cognitive psychology, adult studies generally have a greater availability and reliability of diverse measurement tools, and convergence across these measures, compared to

studies with infants or young children. Additionally, adult experiments can often introduce subtle experimental manipulations to observe more elusive response changes. With these advantages, cognitive theories built on adult studies often include more detailed accounts of information processes and functions related to a specific cognitive task.

Unfortunately, the descriptive theories based on adults generally are not readily applicable to children since children and adults may represent and process information differently due to fundamental changes in learning and development (Shultz, 2003; Sylvain Sirois & Shultz, 1999). In addition to these fundamental differences, experimental procedures used in adults and children often differ in essential and immeasurable ways. One central disparity, as mentioned previously, is that developmental studies often track what infants and children can and cannot do at different stages of development, despite the fact that these cans and cannots often change with experimental manipulations. In contrast, adult studies focus on behaviours that are generalizable between individuals and across different experimental conditions.

Mareschal (2010) argued that the lack of available tools to elucidate *causal mechanisms* of observed behaviours in infants and children (from moment-to-moment observations within a study, to gradual changes throughout development) can undermine the scientific rigor in developmental research. There is growing evidence in the past 20 to 30 years that computational models can be instrumental in bridging between empirical developmental studies and mechanistic explanations of behavioural changes (Elman et al., 1996; Shultz, 2003).

Computational models, particularly those that incorporate temporal, functional and structural constraints, as well as developmental changes, are

particularly useful in accounting for developmental changes. This is because these models often aim not only to understand how information processes result in a specific behaviour, but also to propose explanations as to why a cognitive system gains computational power with development. Of the different types of computational models out there, the connectionist approach is perhaps most commonly employed in developmental research (Mareschal, 2010).

A connectionist model is largely inspired by the processing principles of neural networks. In a connectionist model there are multiple units at different processing layers with input-output relations specified by the associative weights between the units (Fig. 1.1). The activity of the units in the network is modulated by the inputs from the associated processing units. The strength of this input is governed by how strongly the two units in the network are wired together. However, unlike in a real neural network, where the units are either neurons or clusters of neurons, the units in connectionist models of cognitive processes are often assigned subsymbolic meanings—from as small as a specific perceptual attribute (e.g. an angle of a line), to as large an abstract concept as a task goal (e.g. select the red colour). Irrespective to the level of abstractness of each unit, information within the network is processed in parallel. This means that multiple representations are active at any given time, influencing one another. This contrasts with serial processes where a single or a limited number of processes are carried out at a specific stage. In addition to the analogous structure of the model to a neural network, the governing functions such as firing thresholds and experience-dependent changes in connection weights are also similar to the principles of neural dynamics. Learning and development in the model arise from the changes of connections.

These trackable changes provide neurally plausible explanations of how cognitive development may occur.

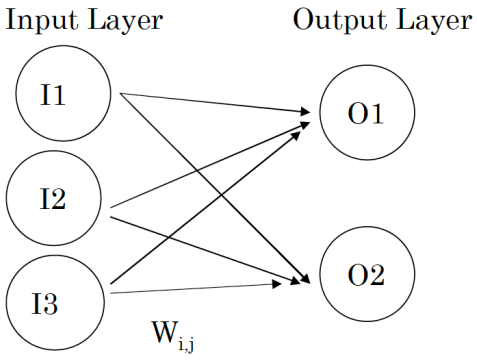

Figure 1.1. Schematic illustration of a two-layer connectionist network. The network has an input layer (I) with three units, which have feedforward weighted connections ($W_{i,j}$) to the output layer (O) comprised of two units.

For these reasons, the current thesis will adopt a connectionist approach to task-switching. Note, however, that because we will focus on tasks that do not involve learning, it is the activation dynamics side of connectionist networks that will be used to model task switching and not the weight dynamics. However, other computational models of task-switching exist. So, in the next section, I will briefly review different computational models for task-switching based on adult studies, before focusing on connectionist model of task-switching by Gilbert & Shallice (2002). All computational models in the current thesis were adapted from Gilbert and Shallice's initial task-switching model.

1.7 Computational models of task-switching

The computational models of task-switching can be broadly classified into normative models and process models. The normative models are models that describe an optimal behaviour under specific theory-driven assumptions, but the behaviours from the model are not grounded by process-based

constraints. A normative model asks: “given a particular theory, what is the optimal level of performance that should be observed?” It does not map real-time behaviours in a given study, and is generally less concerned about the interactions of different processes than a process model. A normative model has clear mathematical specification for each cognitive process.

Meiran's (2000) normative model aimed to understand how inter-trial response conflicts with bivalent response sets give rise to RT cost. In the model, task-associated stimuli and responses each form different mental representations. The RT cost arises because of the similarity/ dissimilarity between the newly calculated response representations and the n-1 response representations. If the representations are similar, then there is a greater response potency than if the two representations are dissimilar. The value of response potency is used to infer how much RT would be slowed. The model focuses on quantifiable interferences between different mental representations, but lacks processes that govern goal activation and maintenance. In contrast, Logan and colleagues’ normative models incorporate different forms of memory retrieval in switching tasks (Logan & Bundesen, 2003; Schneider & Logan, 2005). These authors developed different models reflecting different theoretical assumptions—a model that assumed slow retrieval of task cue from long-term memory (i.e. endogenous control), and a model that assumed a fast priming function from short-term memory. Each cognitive process is governed by specific mathematical equations. They found that performance predicted by the priming model fitted the participant’s data better than the model with endogenous control, and concluded that RT switch costs were largely attributable to interferences. In all, these normative models are concerned with

a specific aspect of the information process in task-switching studies, and generally do not consider effects from parallel processes.

In contrast, process models incorporate multiple processes within the model, and the computations are carried out in time. Notable process-based models for task-switching include (1) Altmann and Gray's (2008) Cognitive Control Model (CCM), which is an activation based *production system* model implemented in the ACT-R system (Anderson, 1996), (2) Brown et al.'s (2007) conflict control model, and (3) Gilbert and Shallice 's (2002) interactive activation model. Both latter two models were connectionist models.

Altmann and Gray's (2008) CCM model simulated a sequence of distinct cognitive processes. The model relied on symbolic representations, such as symbolic memories ('Odd') and production rules (e.g. 'retrieve task goal'). The retrieval of memories and the implementation of production rules are governed by mathematically-based activation functions. These activation functions allowed the network to produce non-linear behaviours since multiple symbolic representations could receive activation at a given time point, and thus the production rules did not necessarily follow a strict sequence. For example, in task-switching, the triggering of a task goal (e.g. parity) will send activations to the associated task concepts (e.g. to even-odd), which in turn will send activations to the associated stimulus (even or odd) and responses (e.g. left or right). Although a wrong production rule can be triggered due to the spread of activations across multiple associated representations, the system overall relies on sequential executions of production rules, in the form of 'if-then' structure. Thus, the model embodies many assumptions on the specificity and time course of each production rule. Finally, although parallel spreading activation is allowed in the model, only one production rule is triggered at one time.

In contrast to the production system process models, Brown, Reynolds, and Braver (2007) constructed a multi-module, multi-layer connectionist model for conflict control, with relatively complex firing thresholds and decay functions for the units in each layer (Fig. 1.2). The network architecture is modular with distinct processing layers corresponding to different cortical structure—a perceptual layer, hidden layer, prefrontal cortex layer (PFC), multiple types of anterior cingulate cortex (ACC) layer, output layer and so on. The model simulated letter/number classification tasks, as in Rogers and Monsell's (1995) study, in which the participants were pre-cued to classify a letter-digit compound (e.g. 'X9') either by parity of the digit, or by the consonant/vowel of the letter, using overlapping response sets. The model fractionated ACC into distinct functions represented by different processing layers. The model focused on the effects of these ACC-associated layers in inter-trial conflict control. It could account for not only the n-1 switch effect, but also higher-order effects (e.g. n-2 repetition or n-2 switch effects). However, for the purpose of our studies, which did not measure higher-order inter-trial effects, the model may be unnecessarily complex at this stage of investigation.

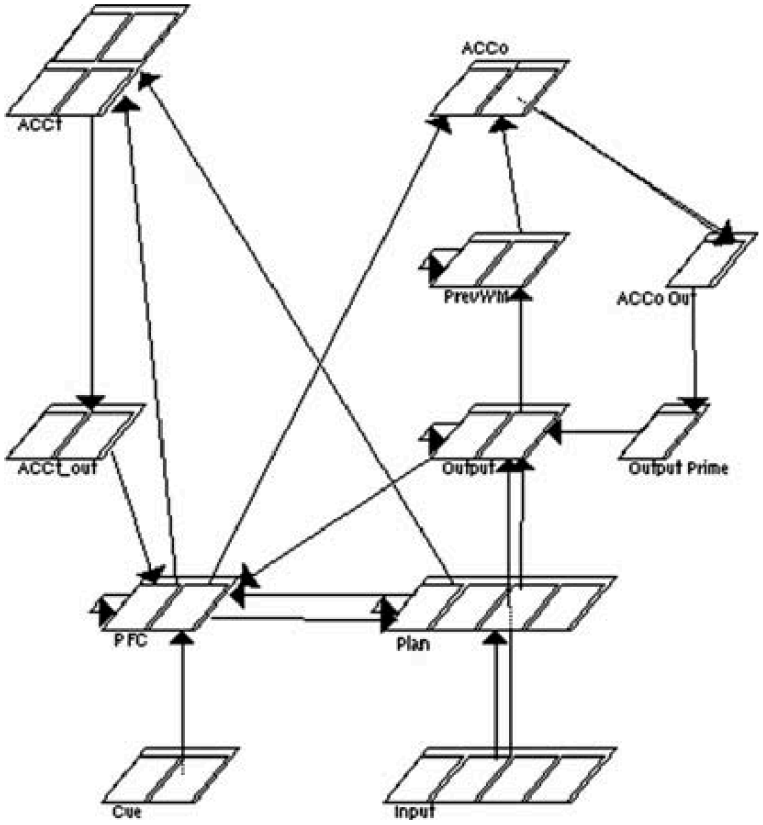

Figure 1.2. Schematic illustration of Brown et al.'s (2007) connectionist model for conflict control. The model comprised multiple modules (e.g. input, cue, prefrontal cortex, different forms of anterior cingulate cortex function), with feedforward connections between the processing layers. The figure was adopted from the original paper by Brown et al.'s (2007).

Gilbert and Shallice's model offer a simpler and more conceptually parsimonious task-switching model (Gilbert & Shallice, 2002), based on the interactive activation framework developed by McClelland and Rumelhart (1981). The model was designed to simulate switching between a dominant word-naming and a non-dominant colour-naming task using Stroop-based stimuli (Fig. 1.3). This model involved a connectionist network with units and fixed weight connections. As in Brown et al.'s (2007) model, there were distinct

processing layers such as a perceptual input layer, a task encoding layer, and an output layer, but the overall architecture was substantially simpler. The mathematical functions in Gilbert and Shallice's model were also fairly straightforward—the units in this model had continuous and accumulative activation values (i.e. each unit is an accumulator of the activations in the associated units), and there was little learning (other than the temporary primes) or representational transformation in the model. In addition to the presence of feedforward connections, as in Brown et al.'s model, there were also lateral inhibition connections between the units in the same processing layer. The purpose of these lateral interactions was to facilitate selection among multiple units (i.e. favouring one unit over the others). A more detailed description of Gilbert and Shallice's task-switching model will be presented in Chapter 5.

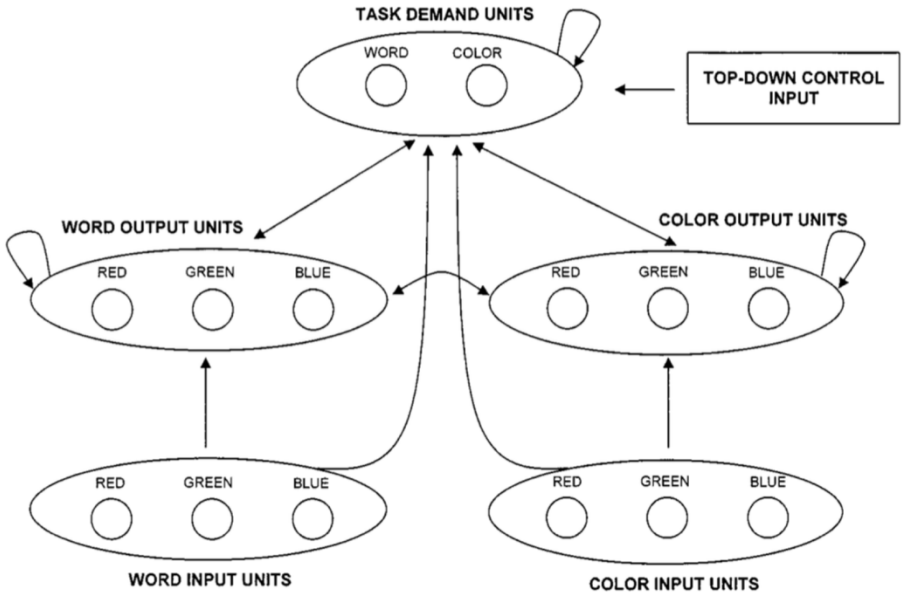

Figure 1.3. Schematic illustration of Gilbert and Shallice's (2002) connectionist model for task-switching with colour/word Stroop tasks. The model comprised three main processing layers (task demand, input, and output). The lateral connections among units in the task demand and output layer are not shown in the figure. The figure was adopted from the original paper by Gilbert and Shallice (2002).

Despite the simplicity of the mode's activation functions and the architecture, many task-switching associated phenomenon were successfully captured by Gilbert and Shallice's model, such as switch costs and priming effects. The model was also able to reproduce the cost asymmetry observed between competing tasks (i.e. larger switch cost to one task than the other), due to the larger top-down signal to compensate for the weaker non-dominant task, compared to the smaller top-down control for the stronger dominant task. Other forms of asymmetric switch costs were also explored, such as asymmetric costs caused simply by differences in connection weights.

The attraction of Gilbert and Shallice's model for us is its context-sensitivity. This means that the model can be easily adapted to different experimental contexts, as has recently been done by others (e.g., Cooper et al., 2018; Sexton & Cooper, 2017). Additionally, since the model involves connection weights, it can potentially be adapted to model development since development in a connectionist network normally involves weight changes (Mareschal, 2010). For these reasons, the interactive activation model of task-switching by Gilbert and Shallice will be adapted for the behavioural studies in the current thesis.

1.8 Overview of studies and models presented in the thesis

To summarise, although the current literature generally reports cognitive inflexibility in young children in experiments that involved a switch in task, developmental studies with experimental designs comparable to adult studies often paint a different picture by reporting mixed findings. However, the use of unfamiliar tasks and of pass/fail performance measures may both have led researchers to underestimate young children's cognitive flexibility. This leaves open to the question whether developmental difference in cognitive flexibility can be observed with continuous measures that tap into the efficiency in goal reconfiguration and in overcoming interferences in simple and familiar tasks, and additionally, in a multisensory environment. In this thesis, I will combine experimental behavioural work with connectionist computational modelling to try to resolve these questions.

Our studies focused on children aged 4 and 6 years, since previous developmental research has identified this as a period of extensive development in cognitive flexibility and control. Crucially, our studies also

include an adult comparison group to ensure that the tasks are suitable for a wide range of ages, rather than just a specific age group. Three behavioural studies were carried out with 4-year-olds, 6-year-olds and adults—(i) a unimodal visual task-switching study (unimodal TS, Chapter 2), (ii) a cross-modal task-switching study with bimodal stimuli (bimodal CMTS, Chapter 3), and (iii) a cross-modal task switching study with unimodal auditory or visual stimuli (unimodal CMTS, Chapter 4). This is followed by four modelling chapters on task-switching (Chapter 5 to 7) and one modelling chapter on the modality shift effect (Chapter 8). The thesis will conclude in Chapter 9 that discusses the main empirical and computational findings. Each of these is previewed in turn below.

1.8.1 Behavioural studies

Chapter 2 describes a first unimodal TS study. This study aimed to understand whether task-switching associated effects change across development. Both pure and mixed task condition were involved in this study. The task sets were adapted from Rogers and Monsell's (1995) study in which the stimulus was composed of two visual elements, and each element could afford either one of the two tasks, or none. The participants were pre-cued to detect specific targets, and to respond by pressing a single response button. In this unimodal TS experiment, both mixing costs and switch costs on accuracy and RT were measured, as well as the overall mean RT and accuracy. A preliminary hypothesis was that younger participants would experience greater mixing costs and switch costs than older participants, since both measures have previously been found to be associated with cognitive control.

Chapter 3 describes a bimodal CMTS experiment. This is a variation to the unimodal TS study but with bimodal stimulus—that is, one of the two elements in the stimulus was a visual input, and the other was an auditory input. The tasks in this experiment were similar to those in the unimodal TS in which the participants were pre-cued to detect targets from a specific category and to respond by pressing a single response button. As with the unimodal TS experiment, both mixing and switch costs were measured. In addition to the task-associated effects, in this experiment, I also explored the modality shift effect (MSE), its interaction with development, and if there was any asymmetry in the MSE as reported in Lukas et al (2010) in adults.

Chapter 4 describes the unimodal CMTS study. This experiment involved stimuli and task instructions that differed from the previous two experiments. All stimuli were unimodal but the modality of the stimulus changed randomly from trial to trial. Here, I examined whether the MSE was a robust phenomenon even when no cross-modal distractors were present, and further studied whether there was a subadditive effect (or not) when both task and modality switched. New target categories were used in the experiment, in order to examine the generalizability of previous experimental findings. Unlike the previous two experiments, the tasks were not pre-cued thus no preparation window was allowed. This allowed the examination of the bottleneck of the attentional system when both task and modality changed, since the participants were not able to reconfigure either information processes before the stimulus onset. These effects were also explored across development.

1.8.2 Computational models

Chapter 5 to Chapter 8 report on computational models of the empirical findings in bimodal CMTS (described in Chapter 3). We chose the behavioural results in bimodal CMTS to be our main focus for the modelling work because it encompassed the largest number of different experimental conditions investigated in the current thesis—pure trials, repetition trials, switch trials, modality-shift trials, modality-repetition trials, and asymmetric pathways (i.e. modality-response compatibility). These different experimental conditions allowed us to explore information processes relevant to those trials.

Chapter 5 includes the bulk of the details on how our models were adapted from Gilbert and Shallice's (2002) original task-switching model. The models in Chapter 5 were the simplest in architectural complexity, and were designed closely to the models described by Gilbert and Shallice. The model architecture involved both fixed feedforward connections and temporary priming connections between the stimulus and the task attribute. This chapter introduced different network ages (Young, Middle and Old) that were architecturally identical but different in connection weights. The models in Chapter 5 captured RT mixing costs, RT switch costs, and RT priming costs on switch trials, but failed to produce the correct error profiles. Moreover, all RT costs were substantially larger in the younger networks than in either the Middle or Old networks.

Chapter 6 explores other reactive mechanisms that might be particularly relevant to our behavioural study. The first mechanism is involuntary reactive task retrieval. Tasks may be retrieved reactively without the mediation of top-down control since both task attribute and the stimuli themselves are closely aligned in the representational space (e.g. a dog picture on a 'dog detection'

task). This reactive mechanism is modelled by introducing additional fixed connections between the stimulus units and the corresponding task attribute units. The second mechanism is involuntary reactive response from the previous primed stimulus-response association. This reactive response was modelled by introducing priming connections between the stimulus units and the response units at the end of the trial. The models in Chapter 6 were successful at reducing RT switch costs and increasing errors in younger networks, but these effects (i.e. cost reduction and error increase) soon achieved an asymptotic level. The simulation results were still some way away from the observed behavioural data.

Chapter 7 introduces additional decay functions and additional parameters that simulated individual differences between networks. The models assume that the activity to both task relevant and irrelevant attributes starts to decay once the task cue disappears—task-relevant attribute becomes less excited, and task-irrelevant attribute becomes less inhibited. Although task attributes decayed after stimulus onset, the networks could probabilistically re-update the task attribute units during the stage of response settling. This intermittent task update is conceptually equivalent to verbal self-reminder. The models assume that the variation of update probability was a matter of individual difference, and not of between-age difference. The chapter also explores whether different ages might be more or less likely to employ a *reactive task strategy* or a *proactive task strategy*, which was defined by how the participants modulated their control by trial types. In the models, task strategies were implemented by varying the top-down signals within a network. The addition of decay, update probability and task strategies allowed the models to generate greater RT and accuracy variations on all trial types. The

models in Chapter 7 explore how the empirical data, which contained various forms of inter-group differences and individual differences, can be captured with the existing model architecture.

In contrast to the previous models that explore task-associated effects, Chapter 8 presents two different models that explore the modality shift effect (MSE), as well as the observed asymmetry of MSE to visual and auditory targets. The two models were based on different theoretical accounts for MSE—a model based on priming effects (priming model) and a model based on carry-over effects from additional modality attribute representations. Both models were able to produce a MSE as well as asymmetric MSE patterns in the networks that simulated the pure task blocks. However, only the model with modality attribute units was able to capture the effect with statistical equivalence to the observed behavioural data in the pure blocks. None of the models were able to capture the asymmetric MSE patterns in the mixed task blocks. The model results suggested that MSE is likely to be a composite effect of multiple processes and could, therefore, change with the information processes involved in the overall task context.

Finally, Chapter 9 concludes with a general discussion and with suggestions for future research. Specifically, the discussion will focus on the empirical findings relating to between-condition mixing/switch costs as well as inter-group differences in overall accuracies. This will be followed by a discussion of the empirical findings on modality dominance and modality shift effects, and whether processes related to modality-specific representations were part of an overall task set. These behavioural findings will be explained by key mechanisms from the computational models; namely, goal activation, carry-over effects from task-associated representations, and carry-over effect from

modality-associated representation. The discussion will also highlight the potential pitfall in defining a task set from the ideal external specification without probing into the internal representation of the task set. Any discrepancy between the desired and actual representation of a task set can generate very different behaviour patterns, particularly in younger participants. Lastly I will talk about modality shift effects and why these effects can be elusive and are particularly context sensitive. I will also highlight the limitation of the models in the thesis, and other additional mechanisms that are worth considering. Finally, the thesis will end with the suggestion that future developmental studies should address the developmental and individual differences in stable performance, in addition to flexible behaviours.

Chapter 2. Experiment 1: Unimodal task-switching (Unimodal TS)

The study described in this chapter explores the usefulness of the task-switching paradigm in understanding cognitive flexibility in 4-year-olds, 6-year-olds, and adults. More specifically, it explores the use of unimodal visual stimuli in a simple target detection tasks.

2.1 Introduction

The current study is inspired by the task-switching paradigm commonly employed in the adult studies. This paradigm is well-established and involves switching frequently between two simple cognitive tasks, each of which requires attention to a different attribute of the stimuli presented, such as colour or form of a letter sequence (Allport et al., 1994; Gade & Koch, 2007; Meiran & Kessler, 2008; Rogers & Monsell, 1995; Rubin & Meiran, 2005). Despite the simplicity of this task, active cognitive control is still necessary for successful performance. The paradigm also allows the comparison between experimental blocks that either involve task-switching (i.e. a mixed task block that involves multiple task rules) or not (i.e. a pure task block that involves only one task rule) (see Chapter 1, section 1.4 for more details). The inclusion of both pure and mixed blocks yields two types of processing costs—global *mixing cost* and local *switch cost*. Global mixing costs refer to the between-block differences in reaction times/accuracy when multiple tasks are involved in one block (e.g., mixed block; switching between responding to colour and form in the sequence), compared to a block where only one task is involved (e.g., pure block; responding only to colour or form). Importantly, these mixing costs are observed even when the

participant is repeating the same task from the previous trial in a mixed block, when no attentional shift is required. Local switch costs refer to the differences found by comparing task-switch trials with task-repetition trials in a mixed block, when attention has to be redirected to activate the new task rule and the associated stimulus-response mappings.

Since the events on pure trials (i.e. in the pure block) and task-repetition trials (i.e. in the mixed block) were perceptually equivalent, the differences in RT between these trial types were believed to reflect the differences in how the task components are represented internally the first place (Los, 1996; Rubin & Meiran, 2005; Steinhauser & Hübner, 2005). Specifically, the differences lie within the selection difficulty among the mixed task components, as it was found that increasing the level of stimulus ambiguity increased mixing costs, but not the number of task rules (Rubin & Meiran, 2005; Steinhauser & Hübner, 2005). It is believed that additional cognitive processes are involved in managing stimulus ambiguity in the mixed block (Tarantino et al., 2016; Wylie et al., 2009).

In contrast, events on task-repetition trials and task-switch trials are different, since on switch trial there is an additional task cue that signals a change in task. However, both trials are grounded in the same overall task structure (i.e. mixed block). The difference in RT between these two trial types are likely to reflect inter-trial dynamics. Specifically, RT switch cost is believed to reflect additional cognitive operation in reconfiguring task sets, as well as the carry-over effects from the previous trial(s) (for review, see Kiesel et al., 2010).

Since both mixing costs and switch costs have been associated to control mechanisms, it is reasonable to expect that these between-condition measures may index developmental differences in cognitive control. Yet, as we have discussed in Chapter 1 (Section 1.4.2), developmental studies on global

mixing costs and local switch costs often report mixed findings on the age effect (Chevalier et al., 2015; M. C. Davidson et al., 2006; Dibbets & Jolles, 2006; Ellefson et al., 2006; Kray et al., 2008; Reimers & Maylor, 2005). However, with the exception of Dibbets and Jolles' study, most of these studies either involved children older than 6 years, or report a low overall accuracy with children younger than 6 years (i.e. <80%). As a result it remains unclear whether the paradigm is also suitable for children as young as 4 years, and whether the between-condition mixing and switch costs are useful index of cognitive controls in early childhood.

2.1.1 The current study

The current experiment was designed not only to measure task-switching costs in preschool children, but also to create a paradigm that connects both child and adult performance. This was achieved by adopting an age-appropriate procedure, with minimal cognitive conflicts, to ensure high accuracy among the youngest participants. The task also requires attentional control in order to select, maintain and switch between task sets. Despite the low level of task-difficulty and conflicts, the core principle of the task-switching procedure remains. It is hypothesised, therefore, that both mixing costs and switch costs will occur. In relation to developmental differences, it is posited that mixing costs will reflect the stimulus ambiguity and the demand on sequential selective attention. With an appropriate level of stimulus ambiguity, both children and adults should have little difficulty in selectively attending to the task-relevant attributes, and are therefore likely to exhibit similar mixing costs. An alternative to the stimulus ambiguity account is the working memory explanation of mixing costs which predicts an effect of development on mixing costs because working

memory has a protracted developmental trajectory to adolescence (Gathercole, Pickering, Ambridge, & Wearing, 2004).

We also investigated the effect of development on switch costs. Here, we hypothesised that if the switch costs reflect cognitive control processes (e.g. task-reconfiguration and/or inhibitory control), then younger participants would experience greater switch costs than older participants.

In the current study, we focused on both preschool children aged 4 and 6 years, and adults. Given the significant changes in cognitive control in preschool years, it is particularly interesting to understand the processing costs associated with attentional shifts in this age group.

2.2 Methods

2.2.1 Participants

Eighty-two participants took part in the study: thirty-four 4-year-olds (18 males, mean age=4.55 years, SD=.26 years), twenty-six 6-year-olds (15 males, mean age =6.28 years, SD=.25 years), and twenty-two adults (8 males, mean age =29.86 years, SD=9.17 years). Children with outlier performances were excluded from the final set of analyses (seven 4-year-olds did not meet this inclusion criterion, see Result for details). All children were recruited from local primary schools and all testing was conducted in a quiet room at the participant's school. Children were given token rewards (i.e. stickers) at the end of each block to maintain their motivations. Each session lasted around 30 minutes. Adult participants were recruited from the University campus. No rewards were given to adults and they were tested in a quiet corner of the University campus. Informed parental consent was obtained for each child participant and informed consent from each adult participant in accordance with

the University ethics committee guidelines. All participants had normal or corrected to normal vision and hearing.

2.2.2 Stimuli and design

The current study employed an intermittent cued task-switching procedure with alternation-runs (i.e., the task switched every four trials). There were two detection tasks. Four categories were involved in the stimulus set (dog, cat, car and boat). Two of those (dog and car) formed the target set for the detection tasks while the remaining two formed the non-target set. The detection task involved 10 greyscale real-life photos in each category, totalling 40 photos. Participants were seated approximately 40cm in front of a 15.4" Macbook Pro. Each task was cued explicitly with a line drawing (measured approximately 5.5cm x 4.2cm), presented centrally on the screen against a grey background before the onset of stimulus presentation. Each stimulus consisted of paired photos (each measured approximately 4.5cm x 4cm) chosen randomly from the target and the non-target sets (e.g. a dog photo paired with a boat), but never from the same category (e.g. there were never two dog photos). The two photos were presented centrally in a white rectangular frame measuring 10.5cm x 5.3cm. There were four trials after each cue. A smaller version of the cue (approximately 3.5cm x 2.7cm) was shown throughout the run, and was placed above the rectangular frame. Participants were instructed to respond to the stimulus by pressing the spacebar whenever the stimulus contained a task-relevant target, and to withhold the response if no target was detected. The spacebar was marked with a green sticker for saliency. This procedure is similar to a Go/No-Go task as the non-target signalled 'No-Go' and the target signalled

'Go'. There were two block types in this experiment, pure task blocks (2 blocks, 40 trials each) and mixed task blocks (2 blocks, 40 trials each).

An auditory feedback with a cash register 'kerching' sound lasting 300ms at 32,000Hz, and at approximately 45dB was played through closed-back headphones when the participant made a correct positive or a correct nonresponse during the testing session. The feedback was immediate for correct positive response, and 3700ms after the stimulus onset for a correct nonresponse.

2.2.3 Procedure

All testing was implemented using Matlab R2014b and Psychophysic Toolbox extensions (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). The experiment was divided into three parts—a demonstration session, a practice session and the testing session. The demonstration and the practice sessions were conducted with Microsoft PowerPoint. Neither the demonstration nor the practice sessions were timed, in order to allow opportunities for explanation and correction. There were 8 trials each for the demonstration and practice sessions, with 4 consecutive trials of the dog game and 4 consecutive trials of the car game. The presentation sequence in the demonstration and practice trials was pre-determined and the stimuli came from the actual stimulus set. Children were told that they were going to play a game that involved looking for certain items—whenever they saw a drawing of a dog/or car (task cue), they would be playing the dog/or car detection game. On each trial, the child was instructed to press the button if they saw a target photo, and to withhold their response if no target was present. The experimenter was free to clarify the task rules as much as possible during the demonstration phase. At the end of the

demonstration the experimenter queried the child about the rules. During the practice session, the experimenter gave additional verbal prompts at cue onsets ('This is a dog/car game') and on each trial ('If you see a dog/car, press the button.'). During practice, the experimenter could also repeat the trial if the child made an error.

The experiment consisted of four blocks. The first two blocks were pure blocks, consisting of one task in each block (e.g. one block of the dog game and one block of the car game), counterbalanced across participants. The final two blocks were mixed blocks, which involved switching between the car and dog games every four trials (Figure 2.1).

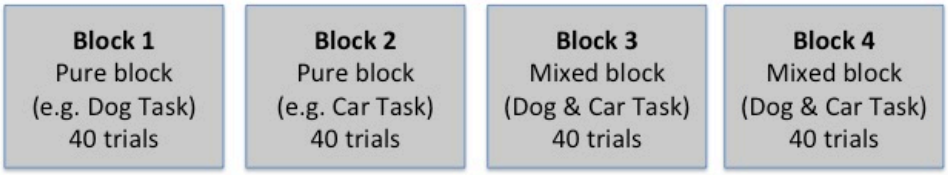

Figure 2.1. Order of blocks in unimodal TS.

Simple auditory feedback was given for correct positive responses and correct nonresponses. A task cue was presented every four trials in both pure and mixed blocks. The test phase consisted of 160 trials equally spread across the blocks separated by a motivation screen to allow for a rest-break if needed. Targets appeared in 60% of the trials in both block types. The task switched every four trials in the mixed block: the trials preceded by a task cue in the mixed block were *switch trials* (switching to a different task from the previous trial), and the trials not preceded by a task-cue were *repetition trial* (repeating the same task as the previous trial). Sixty percent of the switch trials in the mixed blocks were target-positive. Children saw the cue for 3000ms, followed

by a 1000ms cue-stimulus-interval (CSI) showing a fixation cross. A stimulus appeared in the centre of the screen and remained until a response was made or timed out after 4000ms. The inter-stimulus interval (ISI) and response-cue-interval (RCI) varied depending on the response—for a correct response, the interval was 1000ms; for an incorrect response, the interval was 2500ms to allow a recovery period. A fixation cross was shown during the ISI and RCI. A 300ms auditory feedback sound was given for a correct answer (immediately after a correct positive response, or 3700ms after the stimulus onset for a correct nonresponse). Figure 2.2 illustrates the experimental procedure.

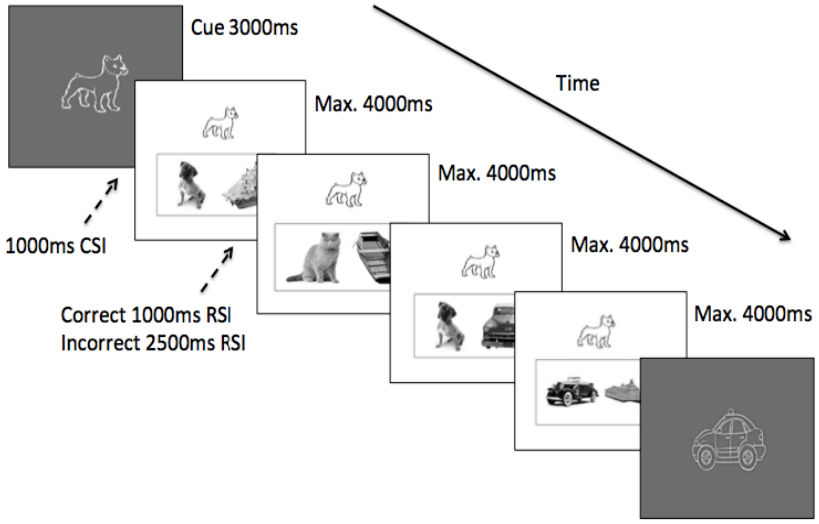

Figure 2.2 Experimental design in the mixed block. CSI: Cue-stimulus interval, RSI: Response-stimulus interval.

2.3 Results

Both reaction time and accuracy were measured in this study. A series of analyses of variance (ANOVAs) were carried out to determine the between-subject effect of Age and Gender, and the within-subject effects of Block Type (pure vs. mixed blocks), and Trial Types (switch trial vs. repetition trials). The first four trials in each block were excluded from the final data since they do not

correspond well to a specific trial type (i.e. the first trial in a mixed block was not a switch trial; and the repetition trials in a mixed block can be executed without referring to multiple task rules). Only correct positive responses were included in the RT analyses. Trials with an RT of less than 300ms were considered as anticipatory errors and were therefore excluded, and the response window was capped at the onset of the auditory feedback (3700ms after the stimulus). The current study made no assumption about the distribution of the RT samples for each participant. Instead, the mean RTs of each participant were obtained by resampling the RT data for 5000 times to bypass the distribution problems (Bollen & Stinet, 1990). The case for adopting a bootstrap method is particularly valid with the limited RT samples as in the current experiment (Mean number of RT samples ranged from 9.95 to 30.38 depending on the condition). The alpha level was set at .05 across all planned comparisons. Unless reported otherwise, all main effects of Age in the analyses reported below were significant at $p<.01$ level.

When testing such young children, there will always be participants who do not adhere to task instructions, for whatever reasons. Rather than choosing a pre-defined fixed level of performance as a cut off, we now adopt a cumulative probability method that allows the group to determine what the level of acceptable performance is by aiming to include ~95% of the participants. The level is set at 70% accuracy threshold in terms of a group-level performance. In our sample, 94% of participants reached this level of performance (Mean accuracy=90.09%, SD=12.88%). The cumulative probability method allows us to exclude participants with extreme performance while also letting the sample determine what the representative level of performance is. This resulted in the

exclusion of seven 4-year-olds, leaving data from 27 four-year-olds (Male=15), 26 six-year-olds (Male=15), and 22 adults (Male=8) for the analyses.

2.3.1 General Accuracy and RT on overall performance

Gender and Age were entered as between-subject factors for the analyses of variance on Accuracy and RT. The main effect of Age was significant for both Accuracy ($F(2,69)=82.86$ $p<.001$) and RT ($F(2,69)=9.07$, $p<.001$). All age groups achieved high accuracy, but older participants were both more accurate and faster than younger participants (4-year-olds: Mean(SE)=89.5(1.6)%, 1552(48)ms; 6-year-olds: Mean(SE)=93.3 (1.4)%, 1211(49)ms; adults: Mean(SE)=98.0(0.4)%, 734(33)ms). There was no main effect of Gender on RT ($p>.600$), or Accuracy ($p>.070$); nor was there an interaction between Age and Gender ($ps>.400$).

2.3.2 Mixing costs

The mixing cost was determined by comparing performance on the trials not preceded by the task cue in the pure blocks, to the repetition trials in the mixed blocks. As shown in Figure 2.3, RT was longer and error rates were higher in the mixed blocks than in the pure blocks across all age groups.

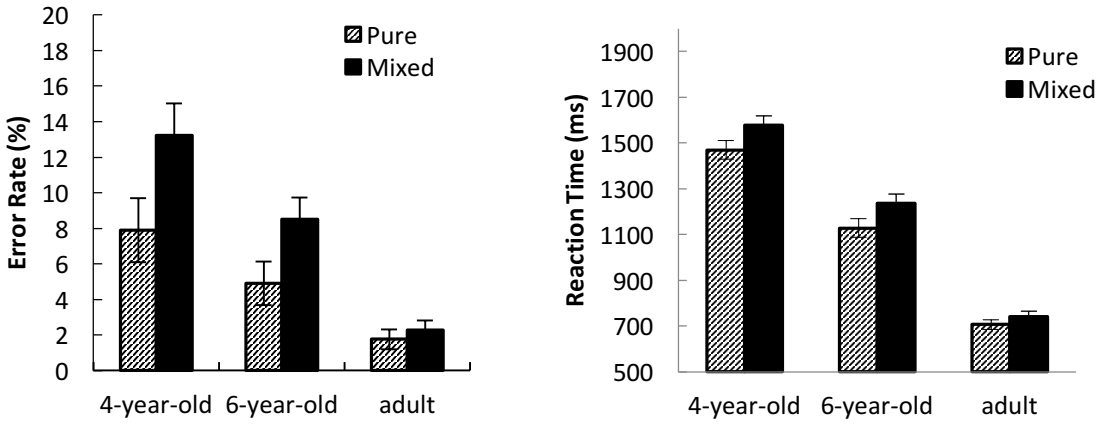

Figure 2.3 Mixing Cost: Left Panel—reaction time in the Pure blocks and the Mixed blocks in different age groups; Right Panel—error rates in the Pure and the Mixed blocks. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

Two separate repeated ANOVAs were carried out on RT and Accuracy, with Age (4-year-olds, 6-year-olds and adult) as the between-subject factor and Block Type (pure vs. mixed) as the within-subject factor. This revealed a significant effect of Block Type on both RT ($F_{RT}(1,72)=14.99$, $p<.001$, $\eta^2=.172$) and Accuracy ($F_{ACCU}(1,72)=14.98$, $p<.001$, $\eta^2=.172$), indicating global mixing costs on both RT ($M_{pure}(SE)=1127(44)$ms; $M_{mixed}(SE)=1214(47)$ms) and on Accuracy ($M_{pure}(SE)=94.94(.71)$%; $M_{mixed}(SE)=91.62(1.11)$%). There was a marginally significant Age by Block Type interaction on Accuracy ($F_{ACCU}(2,72)=2.92$, $p=.060$, $\eta^2=.075$), but not on RT ($p>.300$). Further analyses

revealed that the effect of Block Type on Accuracy was significant for 4-year-olds ($F_{ACCU}(1,23)=7.54$, $p<.020$, $\eta^2=.247$), and 6-year-olds ($F_{ACCU}(1,25)=8.4$, $p<.010$, $\eta^2=.251$), but not adults, $p>.300$.

We also examined the types of errors contributing to the lower accuracy in the mixed blocks. Due to the low number of error trials, non-parametric Wilcoxon Signed-Rank tests for each age group were conducted to examine the number of omission errors (missing targets) and commission errors (false alarm). Adults were excluded from the analyses as there was a large number of ties (>10). Four-year-olds and six-year-olds did not exhibit significant differences in omission error between pure and mixed blocks (*ps*>.100). In contrast, the commission errors were significantly greater in mixed blocks than in pure blocks for 4-year-olds ($Mdn_{pure}=1$, $Mdn_{mixed}=5$, $Z=-2.70$, $p<.007$), and 6-year-olds ($Mdn_{pure}=1.5$, $Mdn_{mixed}=2$, $Z=-2.703$, $p<.007$).

2.3.3 Task-switch costs

Switch trials and Repetition trials in the mixed blocks were entered into the analyses. RTs were longer on the switch trials across all age groups, but the accuracy rates were comparable across trial types (Figure 2.4). Two separate repeated ANOVAs were carried out on RT and Accuracy, with Age (4-year-olds, 6-year-olds and adult) as a between-subject factor and Trial Types (repetition vs. switch) as a within-subject factor. The participants were significantly slower on Switch Trials than on Repetition Trials (F_{RT} (1, 72)=20.59, p<.001 , η^2=.222), indicating a local switch cost on RT ($M_{rep.}$(SE).=1214(47)ms; $M_{swi.}$(SE)=1341(58)ms). But no significant difference between Trial Types was found on Accuracy (p>.500). The Age X Trial Type interaction was not significant on either RT (p=.089) or Accuracy (p>.500).

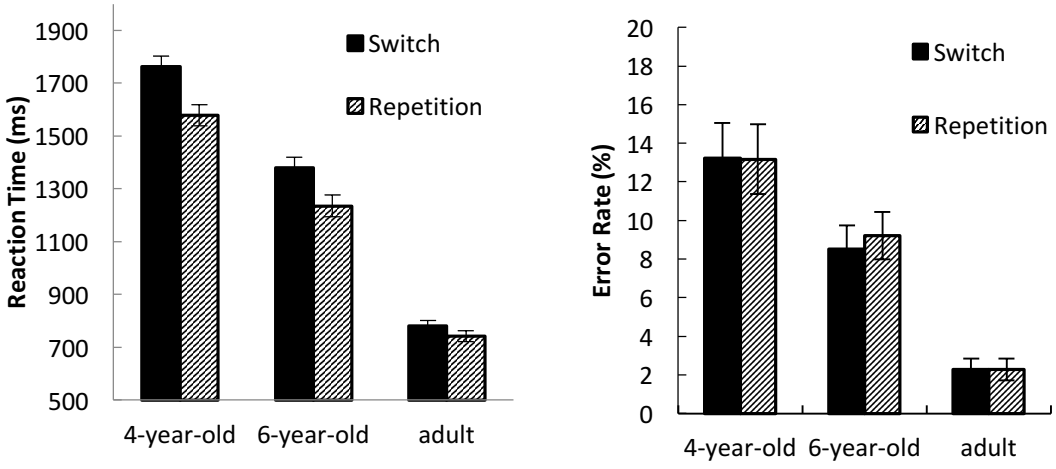

Figure 2.4. Switch Cost: Left Panel—reaction time in the Repetition Trials and the Switch Trials in different age groups; Right Panel—error rates in Repetition Trials and Switch Trials. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

2.3.4 Response-repetition effect

Only trials that were not preceded by a task-cue were included in the analyses of response repetition effect (i.e. pure trials and repetition trials). The participants were quicker at making a response when it was preceded by a response than when preceded by a nonresponse (Figure 2.5). A repeated ANOVA was carried out with Age (4-year-olds, 6-year-olds and adult) as a between-subject factor, and Trial Type (single response vs. repeated response) and Block Type (pure vs. mixed) as within-subject factors. The overall ANOVA revealed a significant main effect of Trial Type ($F(1,72)=42.32$, $p<.001$, $\eta^2=.370$) and Block Type ($F(1,72)=10.53$, $p<.002$, $\eta^2=.128$). Younger children experienced a greater response repetition effect than adults (Trial Type X Age: $F(2,72)=4.26$, $p<.020$, $\eta^2=.106$). Follow-up analyses revealed that both 4-year-olds and 6-year-olds experienced a significant response repetition effect ($ps<.001$, $\eta^2 >.400$), but not adults ($p>.050$). There was an interaction of Trial Type X Block Type ($F(2,72)=23.41$, $p<.001$, $\eta^2=.245$). No three-way interaction was found ($p>.100$).

The Trial Type X Block Type interaction was further explored using one-way ANOVAs separated by Trial Type, with Block Type as the within-subject factor. These analyses revealed that the effect of Block Type (pure vs. mixed) was only evident in the single response trials ($F(1, 74)=33.51$, $p<.001$, $\eta^2=.312$), but not in the repeated response trials ($p>.600$). This finding suggests that RT mixing costs might be largely attributable to RT increase in the single-response trials in the mixed blocks, but not in the repeated-response trials, and the pattern was similar across all ages.

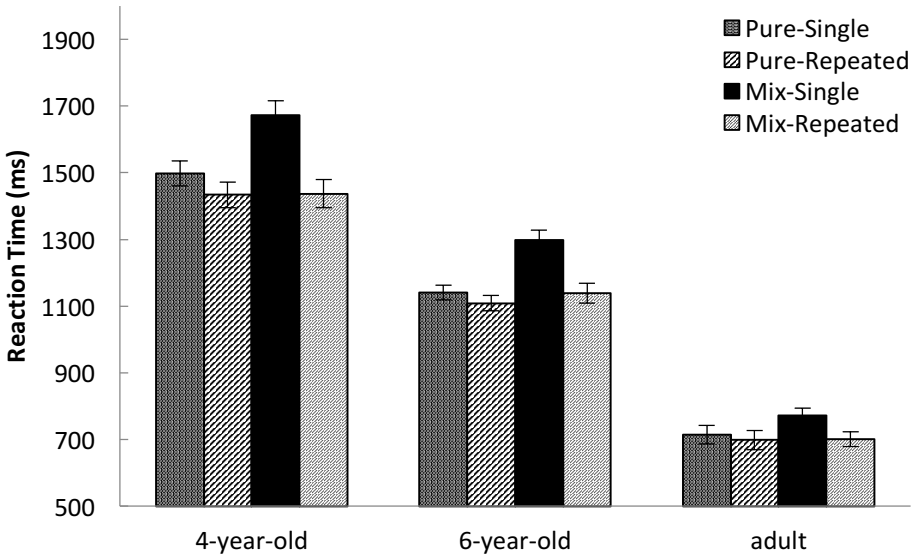

Figure 2.5. Response Repetition Effect in the Pure and Mixed blocks: Single Response vs. Repeated Response. Error bars represent within-subject 95% confidence intervals of means in Pure and Mixed blocks (Cousineau, 2005).

2.4 Discussion

The current study has investigated developmental differences in processing costs using a task-switching paradigm with a child-friendly novel design similar to a Go/No-Go detection task. The task yielded high accuracy rates— with 27 out of 34 in the youngest group achieving a mean accuracy score of 89.5% or above. The task was therefore suitable for measuring both RT and accuracy scores in children as young as 4 years of age, as well as adults. Having established the age-appropriateness of the experimental design, the current study investigated the impact of age on mixing cost, switch cost and response-repetition.

Both children and adults were slower in the mixed-task blocks than in the pure-task blocks. However, age did not interact with RT mixing costs, suggesting that RT mixing costs do not load heavily on cognitive control

components known to develop across this age range (e.g. working memory). Instead, the current study provides support for the view that RT mixing costs reflect some elements of the *selection* processes involved in multitasking. In the current study, the task attributes are easily separable (i.e. the targets were not compound stimuli); consequently, there was a reduced demand on selective attention. In this context, we found that preschool children did not find it harder to manage two tasks than adults, at least in terms of RT costs related to switching between tasks. It thus appears that the efficiency in dealing with multiple tasks and the ability to attend selectively to simple task attributes are present in the preschool years, particularly when the tasks and stimuli are age-appropriate. This finding is comparable to Dibbets and Jolles's (2006) study, in which a child-friendly version of a task-switching experiment also found no age effect on RT mixing costs (from 4 to 13 years old). These findings raise some questions about the developmental effect on mixing costs reported in other studies (e.g. Cepeda, Kramer, & Gonzalez de Sather, 2001; Davidson, Amso, Anderson, & Diamond, 2006). In particular, it is unclear if the developmental effect on mixing costs reflect developmental differences in cognitive control, or instead, reflects experience-dependent understanding of task structures and stimulus/response attributes, and/or the efficiency in translating stimulus into response execution (c.f. Ridderinkhof, van der Molen, Band, & Bashore, 1997). Interestingly, the RT mixing cost was evident only when the response was not repeated in the previous trial. Thus, whatever the difficulty in the mixed blocks was, it could be overridden easily by the facilitative primes. While the pattern of response repetition facilitation was evident across all ages, our analysis showed that preschool children experienced a greater response repetition effect than adults. This is consistent with Crone et al.'s (2006) finding that children

experience a greater effect from transient stimulus-response associations. However, due to the lower resolution with Go/No Go procedure, compared to the choice procedure, response repetition in our study is an imprecise index of the associative primes. In our experiment, priming facilitation could come from stimulus value-response associations, stimulus category-response associations, task goal-response associations and/or other forms of multi-way associations. It is not known if children experience a greater level of priming effect at all levels, or from a specific form of primes, compared to adults.

Although there was no age interaction effect on RT mixing costs, a moderate age interaction effect was found for accuracy mixing costs. Specifically, 4- and 6-year-olds made more commission errors in the mixed blocks than in the pure blocks. If the poorer performance in the mixed blocks was due to working memory demands, such that the children had difficulties in maintaining the relevant goal state, then we would expect an increase in both omission and commission errors. Instead, the increase in commission errors alone indicates that the reason behind the errors is due to 4- and 6-year-olds' failure to override responses to task-irrelevant attributes, which could be underlain by an inhibitory deficit. The overall result is also consistent with the presence of a larger response repetition effect among preschool children than adults. Goschke (2000) argued that the level of response inhibition is in proportion to the risk of perseverative responses (also see Grzyb & Hübner, 2013). While this strategic proportional inhibition-to-interference task strategy might be well practiced by adults, it might not be robustly employed by children. Overall our results suggest that attentional selectivity and interferences are dissociable components. Although preschool children may be equipped with the requisite attentional selectivity and perform well in multi-task condition, they

experienced both greater facilitation and interference from the primed associations, as exhibited in the greater response repetition effect and commission errors.

The RT switch costs were also evident across all age groups, replicating previous findings that switching to another task-set produces reliable RT costs even when allowing a generous preparation time for the upcoming task. Switch costs have generally been taken to reflect additional cognitive processes in task-set reconfiguration (Meiran, 2000; Rogers & Monsell, 1995; Rubinstein et al., 2001), and in development, to other general endogenous factors such as the ability to reflect on changing situations and to inhibit prepotent representations (Cepeda et al., 2001; Diamond et al., 2005). We therefore predicted that preschool children would experience greater switch costs than adults. Contrary to our prediction, we found no age interaction with the RT and accuracy switch costs, indicating that switch costs are not a sensitive measurement of the development of cognitive control. Children as young as 4 years old were effective at preparing for the alternative task prior to the stimulus onset, incurring no cost in accuracy on switch trials as compared to the repetition trials.

Perhaps the combination of a long preparation window, high target discriminability and the overall task simplicity allowed any potential developmental effects to be minimised. However, other studies using more 'traditional' task design and stimuli have also failed to find an age interaction with switch costs (e.g. color/shape task with participants aged 7 to adults [Exp. 1], Ellefson, Shapiro, & Chater, 2006). It seems likely that switch costs are more sensitive to other factors such as the carry-over effect from pre-switch trials, in which the inhibition of the task-set (e.g Mayr & Keele, 2000) and/or the

activation of the n-1 task/stimulus has lingered into the switch trial (Allport et al., 1994). That said, our study demonstrates that young children can clearly switch between different goal states given an age appropriate task and context. The developmental differences in switch costs observed in other studies may reflect differences in carry-over effects rather than the ability to shift between mindsets.

Overall, the current study has found that 4- to 6-year-olds exhibit mixing costs and switch costs in very similar ways to adults. The lack of an age interaction effect on switch costs indicates that children as young as 4 were able to prepare for the task set prior to stimulus onset; while the absence of an age interaction effect on RT mixing costs suggests that, given the current design, children experienced a similar amount of stimulus ambiguity as adults. In sum, the attentional control necessary to perform at least two tasks and to switch between tasks is present in preschool children. Although the attention flexibility in switching between tasks is largely present at the age of 4, there are still developmental differences uncovered in the current study. Younger children appeared to have greater difficulty in overriding an erroneous response that resulted in an increase in commission errors in the mixed blocks; relatedly, they also experienced greater response repetition facilitation. And finally, as expected, younger children were overall slower and less accurate than older participants, irrespective to the trial type. It remains unclear why younger children are less accurate than adults, despite exhibiting the ability to perform a task.

The primary aim of the current study was to investigate the extent to which preschool children exhibit cognitive and attentional flexibility in a multitask context, and whether this flexibility, if present, reflects global mechanisms associated with task-switching and task maintenance, or rather, reflects other

task-specific factors such as the types of stimulus attributes and the ease of translating perceptual information into response selection, as well as general novelty. Since the current study found no age interaction effects on either mixing costs or switch costs, it is likely that previous reports of age interaction effects reflect other processes specific to each task context. The range of attentional and cognitive processes in different task-switching studies is greatly variable, and therefore the cognitive demand to switch task and to multitask can differ greatly between experiments and between age groups. However, by focusing on the most demanding type of task for preschool children (e.g. those that involve novel situation, high working memory and inhibitory demand, and complex stimulus-response translations), preschool children's attentional control may be underappreciated. In all, our study suggests that a task-switching paradigm itself is insufficient to uncover developmental differences in attentional control, and more detailed specifications of processing cost beyond a general measurement of mixing costs and switch costs are needed to understand developmental differences in cognitive control using task-switching procedures.

While the current study was inspired by task-switching studies in the adult literature, it made some major modifications to the experimental design. Most notably, the task took the form of Go/No-Go with a single response, rather than the typical two-button choice task. One may argue that changing the nature of stimulus-response mappings could have a dramatic effect on task conflicts, and therefore masking the developmental differences in cognitive controls in dealing with these task conflicts. It is well known that younger children are poorer at overcoming prepotent responses (e.g. Ridderinkhof, van der Molen, Band, & Bashore, 1997; Simpson et al., 2012; Wright & Diamond, 2014). Stimulus-response conflicts are often inherent in the task-switching

paradigm as most studies employed choice tasks with bivalent response sets. At least one adult task-switching study employed Go-NoGo similar to the current study and found sizeable switch costs (Schuch & Koch, 2003). It was also found that switch costs were dependent on the response execution of the n-1 trial, where a response was necessary to elicit switch costs. Nonetheless, both choice and Go/No-Go designs show a consistent pattern of processing costs. When the level of task difficulty and conflicts are aligned across age groups, there is no strong reason to believe that an age effect on mixing costs and switch costs, if present, would be affected by the decision to adopt Go-NoGo or choice tasks.

In summary, the current study found that preschool children have the attentional flexibility to switch between two competing tasks, incurring no greater between-condition costs than adults. When focusing on RT measures, we found that preschool children did not exhibit greater difficulty at multitasking, nor at moment-to-moment shifts between two different task goals, when the tasks and stimuli were age-appropriate. Our findings suggest that the age effects reported in cognitive flexibility may derive from resolving task conflicts and/or differences in age-related familiarity with the stimuli and the testing context, rather than difficulties in task switching per se.

In Chapter 3, I will explore whether the findings in the unimodal TS study still hold in a multisensory environment, using a cross-modal task-switching study (bimodal CMTS). The bimodal CMTS in Chapter 3 is procedurally equivalent to the unimodal task-witching study in this chapter, making it suitable for direct comparison. Finally, in addition to the task-associated effects described here, our next chapter also explores modality-associated effects such as modality dominance and the modality shift effect (MSE).

Chapter 3. Experiment 2: Cross-modal task-switching with bimodal stimuli (bimodal CMTS)

The current study in this chapter aims to extend the task-switching paradigm to a multisensory context to align better with the real world. Our previous unimodal task-switching study using a simple detection tasks found significant mixing costs and switch costs in all age groups; however, the costs were not moderated by development. It thus appears that young children were as effective as adults in both managing multiple tasks and switching between tasks, at least in a unisensory context. The main objective of the bimodal cross-modal task-switching (bimodal CMTS) is to establish that both mixing costs and switch costs persist in different experimental contexts, including in a multisensory environment, and that both children and adults still exhibit comparable costs in these between-condition measures. Additionally, the current study will explore modality-associated effects, namely modality shift effect and modality dominance.

3.1 Introduction

In this study, we explored whether task-associated effects in task-switching paradigm can be found in multisensory environment. The main aims of the current study are to (1) replicate the task-associated effects (mixing and switch costs) commonly found in unimodal task-switching paradigm, (2) explore the effect of response repetition in different trial types, (3) understand the costs in shifting between modalities, and (4) investigate modality dominance with bimodal stimuli. All these three research objectives will be explored from a developmental standpoint.

Our previous unimodal task-switching experiment showed that young children did not exhibit a larger between-condition mixing and switch costs, compared to adults. Our results suggest a relatively mature ability in multi-tasking and in adaptively responding to environmental changes in young children. However, the experimental paradigm with tasks in a unisensory environment often involve involuntary effects such as stimulus-response primes that may otherwise obscure the cost related to endogenous control in goal shifts and goal representations.

As we have seen in unimodal TS, response-repetition has a facilitative effect in trials where there was no change in task goal. Our unimodal TS experiment has shown that this facilitative effect was greater in repetition trials in mixed blocks than in pure blocks, and greater yet in children than in adults. In fact, the facilitation was so strong that it effectively eliminated mixing costs when comparing primed repetition trials (i.e. repeated-response) with primed pure trials (Fig. 2.5, Chapter 2). Similarly, RT switch costs might also be due to the differences in the priming effects in repetition and switch trials in mixed blocks. Past research has documented that response repetition has a facilitative effect only when the task repeats, but not when the task changes (Rogers & Monsell, 1995). This is due to the fact that in switch trials with repeated responses, there is a change in the associative prime as the stimulus was previously associated to a different task goal on n-1 trial. Therefore, it is likely that, similar to the absence of RT mixing costs between primed pure and repetition trials in the unimodal TS experiment, a major source of RT switch cost was to do with the differences in priming effects (indexed by response repetition) in repetition and switch trials in mixed blocks. In this experiment, we

will examine response repetition effects in different trial types to confirm that priming facilitation is indeed constrained by task.

Since differences in primes are likely to contribute to the overall between-condition costs, one advantage of using cross-modal task procedures is the possibility of controlling for the effects of these task-unrelated involuntary processes, at least at the level of perceptual stimulus. If switch costs in the unimodal TS experiment largely reflected the activation of a supramodal task goal, then switch costs should persist in CMTS, even after within-modal priming facilitation in repetition trials is controlled for. With cross-modal task-switching procedure, we can explore whether switch costs are indeed goal-related and replicable.

Additionally, the present study also explored the other form of attentional shift, namely shifting between modalities. Modality shift effect (MSE) refers to a slowed response when shifting attention from a different modality, compared to attending to the same modality. Currently it is not known about whether MSE can also be a useful index for the development of multisensory attentional control.

There are reasons to speculate that young children may exhibit a different MSE from adults. Specifically, young children appear to deploy attention differently from adults on tasks where independent, potentially inhibitory, cross-modal attention processes are needed (i.e. as opposed to multisensory integration) (e.g. Barnhart, Rivera, & Robinson, 2018; Leary & Sloutsky, 2013; Nava & Pavani, 2013; Robinson & Sloutsky, 2004; Thomas, Nardini, & Mareschal, 2017). On such cross-modal tasks young children often exhibit auditory dominance when attending to audiovisual information, whereas adults typically exhibit visual dominance. The modality dominance effect is the

phenomenon in which the information in the dominant modality overshadows or degrades the information in the non-dominant modalities. Adult visual dominance is well established. For example, Colavita (1974) asked participants to make modality-based choice responses on auditory-only, visual-only or audiovisual stimuli. On audiovisual trials, adults often missed the auditory element and made visual-based errors (Colavita, 1974; Koppen & Spence, 2007; Ngo, Sinnett, Soto-Faraco, & Spence, 2010; Sinnett, Spence, & Soto-Faraco, 2007). In comparison, young children typically exhibit auditory dominance on Colavita-type tasks (Nava & Pavani, 2013; Wille & Ebersbach, 2016), and other induction and detection tasks (Leary & Sloutsky, 2013; Robinson & Sloutsky, 2004; Sloutsky & Napolitano, 2003).

Most research on modality dominance has focused on discrete performance measures such as modality-based errors or other modality-based decisions, because both auditory and visual elements in the bimodal stimuli are typically task-relevant targets. However, modality dominance on continuous measure, such as RTs, has also been reported (Nava & Pavani, 2013; Sinnett, Soto-Faraco, & Spence, 2008). In Sinnett et al.'s (2008) RT-based experiment, the participants were presented with unimodal auditory, unimodal visual and bimodal stimuli intermixed in a series of trials, and were asked to detect targets in one modality only (i.e. auditory-target block vs. visual-target block). On bimodal trials, the cross-modal information is redundant and not task-associated. Intriguingly, the cross-modal effects were different between auditory and visual conditions. Compared to the unimodal targets, visual target detection was quicker with a redundant cross-modal auditory distractor, whereas the auditory target detection was slower with a cross-modal visual distractor. This study found the coexistence of visual dominance (i.e. interference) on auditory

processing as well as auditory facilitation on visual processing. Given that young children are reported to have auditory dominance in error-types and in induction learning (Nava & Pavani, 2013; Robinson & Sloutsky, 2010; Sloutsky & Napolitano, 2003), it is unclear whether this auditory dominance would slow down visual processing in children, or, facilitate visual processing as found in adults.

If young children and adults exhibit different modality dominance, they may potentially exhibit different patterns of MSE. One reason for why MSE may change as a function of modality dominance is because an asymmetric cost is often observed when two processes vary in strengths. For example, an asymmetric cost has been reported in task-switching studies when switching between word and colour tasks with Stroop task stimuli (Allport et al., 1994). Although the asymmetry cost at the task-set level is also possibly caused by greater cognitive control on the weaker task and not simply by the asymmetry in task strengths (Gilbert & Shallice, 2002), at this stage, it remains unclear how modality dominance may interact with MSE.

The first aim of the present study is to replicate the task-associated effects found in the unimodal TS study (Chapter 2)—namely, a significant main effect of mixing cost and switch cost, but no significant developmental differences in these costs. Secondly, the current study aimed to understand the constraints of RT facilitation from involuntary inter-trial events. Thirdly, since the current study employed bimodal stimuli, it also allows for the investigation of RT-based auditory dominance in children and visual dominance in adults. The final aim is to explore the development of the MSE, since no developmental studies have been carried out in this area. In sum, this experiment investigates the cost of switching between different tasks, of shifting between visual and

auditory modalities in a multisensory environment, and the effect of modality dominance on modality shift effects.

3.2. Method

3.2.1 Participants

Thirty-four 4-year-olds (16 males, mean age=4.57 years, SD=.23 year), 25 six-year-olds (16 males, mean age=6.60 years, SD=.28 year) and 26 adults (9 males, mean age=28.51 years, SD=8.26 years) participated in this experiment. All children were recruited from state-funded primary schools in the Greater London, UK, and all testing was carried out in a quiet room at the participant's school. All adult participants were recruited from the University campus, and all testing sessions were carried out in the testing lab. Informed parental consent was obtained for each child participant and informed consent for each adult participant in accordance with the University ethics committee guidelines. Children were given a token reward (i.e. stickers) at the end of each block and a certificate at the end of the study. Adult participants received course credits for participating in the experiment. All participants had normal or corrected to normal vision and hearing. A unimodal baseline task was carried out with a subset of randomly selected participants (11 4-year-olds, eleven 6-year-olds, and 10 adults). Children with outlier performances were excluded from the final set of analyses (9 4-year-olds did not meet the inclusion criterion, see Result for details). Each session lasted around 30 minutes.

3.2.2 Materials

As with the previous unimodal TS study (Chapter 2), the current study employed an intermittent cued task-switching procedure with alternation-runs

(i.e., the task switched every four trials). Most testing sessions were carried out on a 15.4” MacBook Pro (Mid 2012 release). However, 20 out of 26 adults received the experiment administered on a 13” MacBook Air (2013 release) due to equipment shortage. The main differences between the two laptops are the screen size and processing speed. To address the issue of screen size, the image sizes were calibrated to the same dimensions in centimetres in both apparatuses. Processing speed of the system was not thought to be an issue since adult subjects were much quicker than children; the differences in RT caused by processing speed were negligible when comparing performances between age groups. Participants were seated approximately 40cm in front of the laptop.

The experiment consisted of detection tasks with explicit task cues. There were four categories of animals presented in the game—dog, bird, cat, and sheep. For each participant, two of the animal categories were target animals, and the remaining two animal categories were neutral distractors (i.e. not associated with any task goal). Half of the participants played bird-dog detection games while the other half played cat-sheep detection games. The participants were asked to monitor both visual and auditory inputs since the target animal could appear randomly in either modality. They were asked to press the Apple Magic Mouse (i.e. single response key) highlighted with a green sticker upon relevant target detection, and withhold the response if no relevant target was present.

Tasks were explicitly signalled by multimodal cues before the onset of stimuli. The task cues consisted of a line drawing measuring 8cm x 6.7cm and a spoken word at approximately 65dB (e.g. dog drawing with spoken word ‘Dog’). The duration of the visual element of the cue was 3000ms, however the

duration of the auditory element was between 630ms to 750ms as the word was only spoken once. There were 10 different greyscale photos measuring approximately 5.3cm x 4.5cm, and 10 different animal sounds measuring approximately 70-75dB, for each animal category (e.g. a 'cat' set contained 10 different cat photos and 10 different meows). All stimuli were audiovisual and consisted of one visual element and one auditory element randomly selected from the four animal sets. The visual and auditory elements of the bimodal stimulus were always from different categories (e.g. a dog picture paired with a cat sound). A continuous neutral water sound was played in the background at approximately 45dB throughout the experiment, in order to match the continuous presentation of visual information that occurs in these types of experiments.

Figure 3.1 shows the sample stimuli in the experiment. The visual elements of both cues and stimuli were presented centrally on the screen inside a white presentation window measuring 15.8cm x 10.6cm against a grey background. To minimise working memory demand, a smaller version of the task cue measuring 4.5cm x3.7cm was placed above the presentation window as a reminder throughout each trial. The participants were instructed not to look at the peripheral task reminder unless needed. All auditory elements were played through a child-friendly closed-back headphone to both ears at around 70-75dB. A task cue was shown every four trials.

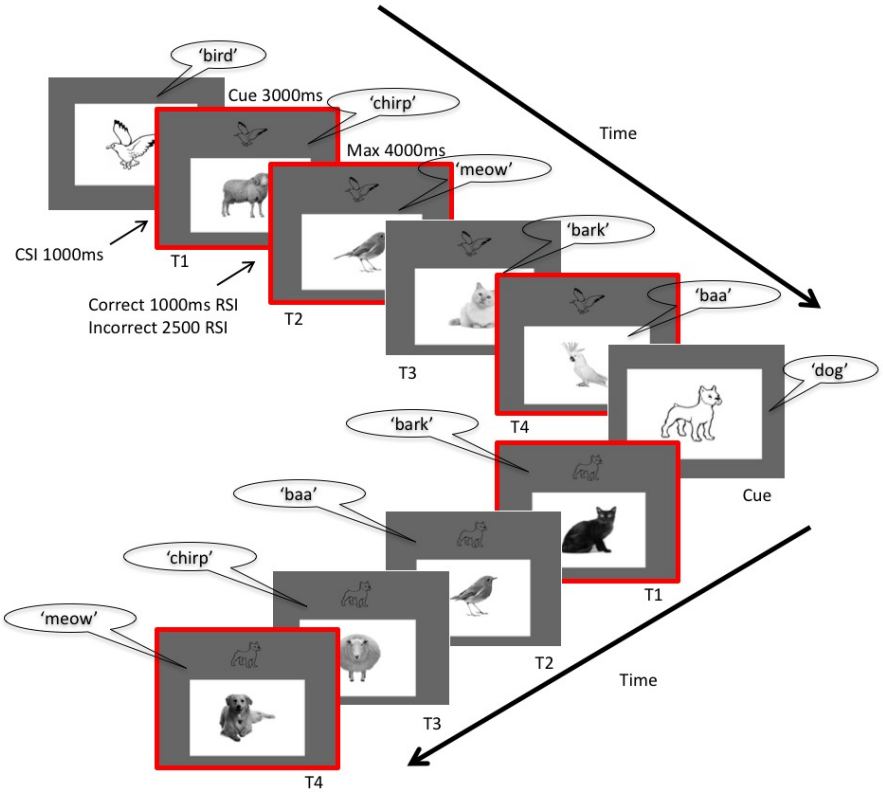

Figure 3.1. Experimental design in the mixed blocks. CSI: Cue-stimulus interval, RSI: Response-stimulus interval. All stimuli were bimodal with one visual element and one auditory element. Trials with a red border were examples of target-positive trials.

An auditory feedback with a cash register 'kerching' sound lasting 300ms at 32,000Hz, and at approximately 45dB was played through closed-back headphones when the participant made a correct positive or a correct nonresponse during the testing session. The feedback was immediate for correct positive response, and 3700ms after the stimulus onset for a correct nonresponse.

In addition to the audiovisual stimuli in the experimental condition, a baseline condition was completed out with a subset of the participants. Using the same stimulus sets as in the experimental conditions, the baseline condition

involved a unimodal detection tasks with a single target category in each block. The aim of the baseline condition was to test the baseline speed for target detection without cross-modal distractors. Performance in the baseline condition will be compared against performance in the pure blocks with cross-modal distractors, in order to examine any modality dominance effects caused by the concurrent cross-modal events. The baseline condition involved four blocks—a unimodal visual block and a unimodal auditory block for each target category (e.g. bird-visual, bird-auditory, dog-visual, dog-auditory), with the order of the target modality counterbalanced across participants. The task cues were unimodal—a visual cue for the visual block and an auditory cue for the auditory block. In the auditory block, a fixation cross was presented in the centre of the screen when the auditory cue and stimuli were presented. In the visual block, the same continuous background neutral water sound was played at approximately 45dB throughout the experiment.

3.2.3 Procedure

All testing was implemented using Matlab R2014b and Psychophysic Toolbox extensions (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). The experiment was divided into four parts—a sound familiarisation session, a demonstration session, a practice session and the testing session. A subset of the participants also underwent a fifth baseline session at the end of the experiment. The baseline session was always carried out at the end in order to prevent practice effects in the main experimental condition—although, as a result, practice from the main experimental condition might have compromised the results obtained in the baseline condition.

The sound familiarisation, demonstration and the pre-testing sessions were conducted using Microsoft PowerPoint. Neither of these sessions was timed, in order to allow opportunities for explanation and correction.

3.2.3.1 Sound familiarisation session

Although all stimuli were likely to be familiar to all ages, because the photos and sounds were chosen carefully to be as transparent as possible, it was still a concern that the participants might be unfamiliar with some of the sounds. Therefore, the aim of the sound familiarisation session was to maximise the likelihood that the participants were able to identify the animal categories correctly by the sounds. The session was for demonstrative purpose only and the participants did not need to respond in this session. However, they were instructed to remember the sounds and were told that the sounds would appear in the game later on. There were two blocks of sounds—one for each target category. The experimenter explicitly stated which animal category the sounds were from at the beginning of the block (e.g. 'I am going to show you sounds from different birds. Listen carefully.'). At the beginning of each presentation the experimenter gave a reminder of the category of the sound (e.g. 'Here comes another bird.'). Each sound lasted for 4 second. All 10 sounds from each target category were presented in the session.

3.2.3.2 Demonstration and practice session

There were 8 trials each for the demonstration and practice sessions, with 4 consecutive trials of one task (e.g. bird) and 4 consecutive trials of the other task (e.g. dog). The presentation sequence in the demonstration and practice trials was pre-determined and the stimuli came from the actual stimulus set. Children were told that they were going to play a game that involved looking

for certain animals—whenever they were shown the task cue (e.g. audiovisual task cue), they would be playing the bird/or dog (or cat/or sheep) detection game. On each trial, the child was instructed to press the Magic Mouse if they saw or heard the target animal, and to withhold their response if no target was present. The experimenter was free to clarify the task rules as much as possible during the demonstration phase, and to use communicative gesture (e.g. 'pointing to the bird'), verbal query (e.g. 'Did you hear a bird?') and verbal encouragement where appropriate. At the end of the demonstration session, the experimenter queried the child about the rules (e.g. 'What should you be looking for when you see the cartoon drawing of a bird?/ How do you tell the computer when you find it?'). The duration of each stimulus was roughly 4 seconds, but the slides were manually controlled by the experimenter.

There were four trials for each task in the practice session. During the practice session, the experimenter gave additional verbal prompts at cue onsets ('This is a bird/dog game') and on each trial ('If you see or hear a dog/bird, press the button.'). If the participant made an error, the experimenter could repeat the trial. No participants were excluded as a result of performance in the practice session; all participants proceeded to the testing session regardless of the performance during the practice session.

3.2.3.3. Testing session

The experiment consisted of six blocks, with 168 trials spread evenly across the blocks separated by a motivation screen between blocks to allow for a rest-break if needed. The first two blocks were pure blocks, consisting of one task in each block, with the order of the tasks counterbalanced across participants. The final four blocks were mixed blocks, which involved switching

between the two tasks every four trials. There were 56 trials in the pure blocks, and 112 trials in the mixed blocks.

A task cue was presented every four trials in both pure and mixed blocks. Trials in the pure blocks involved only one task rule. In the mixed blocks, the task switched every four trials, resulting in two trial types. The trials preceded by a task cue in the mixed block were *switch trials* (switching to a different task from the previous trial), and the trials not preceded by a task-cue were *repetition trial* (repeating the same task as the previous trial). Children were shown the audiovisual cue for 3000ms, followed by a 1000ms cue-stimulus-interval (CSI) showing a fixation cross. The visual element of the stimulus appeared in the centre of the screen, and the auditory element of the stimulus appeared bilaterally to both ears. The stimulus was terminated when a positive response (i.e. button-press) was made or timed out after 4000ms (nonresponse). The inter-stimulus interval (ISI) and response-cue-interval (RCI) varied depending on the response—for a correct response, the interval was 1000ms; for an incorrect response, the interval was 2500ms to allow a recovery period. A fixation cross was shown during the ISI and RCI. A 300ms auditory feedback sound was given for a correct answer (immediately after a correct positive response, or 3700ms after the stimulus onset for a correct nonresponse).

Targets appeared on 64.3% of the trials in either pure blocks (36 out of 56 trials) or mixed blocks (72 out of 112 trials). Half of the targets were visual targets and the other half were auditory targets. In the pure blocks, only one target set appeared in each block (e.g. for participants who were assigned bird-dog as target sets, in the ‘Dog’ pure block, the bird stimulus set was not used, and vice versa). In the mixed blocks, there were different types of target trials—*uni-selection* trials in which only one element was from either target sets and

the other element was from the neutral sets, and *bi-selection* trials in which both elements were from the target sets. Among the 72 target-positive trials in the mixed blocks, 52 target were uni-selection trials, and 20 were bi-selection trials. In both conditions, the visual elements and auditory elements of the bimodal stimulus were from different animal categories.

3.2.3.4 Baseline session

As mentioned previously, only a subset of participants completed the baseline session with unimodal stimuli. The experimental procedure was similar to the pure blocks in the main experiment. There were four blocks in the baseline session—one unimodal visual and one unimodal auditory block for each of the two target category pairs (e.g. bird-dog). The first two blocks were of the same task (e.g. bird-visual and bird-auditory), and the latter two blocks were of the other task (e.g. dog-visual and dog-auditory). The order of the blocks by stimulus modality was counterbalanced across participants (e.g. the visual block followed by the auditory block or vice versa). Each block began with the unimodal task cue (e.g. bird drawing), followed by 12 trials in each block. The target appeared in 50% of the trials (6 out of 12 trials). All cue duration, stimulus duration, CSI, ISI and RSI were the same as in the main experiment.

3.3 Results

Both reaction time and accuracy were measured. A series of analyses of variance (ANOVAs) were carried out to determine the between-subject effects of Age and Gender, and the within-subject effects of Block Type (pure vs. mixed blocks), and Trial Types (switch trial vs. repetition trials). The first four trials in each block were excluded from the final data since they do not correspond well to a specific task condition or trial types (i.e. the first trial in the mixed blocks

was not a switch trial; and the repetition trials in the mixed blocks can be executed without reference to multiple task rules). Only correct positive responses were included in the RT analyses. Trials with an RT of less than 300ms were considered as anticipatory errors and were therefore excluded, and the response window was capped at the onset of the auditory feedback (3700ms after the stimulus).

The current study made no assumption about the distribution of the RT samples for each participant. Instead, the mean RTs of each participant were obtained by resampling the RT data for 5000 times to bypass the distribution problems (Bollen & Stinet, 1990). The case for adopting a bootstrap method is particularly valid with the limited RT samples as in the current experiment. The alpha level was set at .05 across all planned comparisons. Unless reported otherwise, all main effects of Age in the analyses reported below were significant at $p<.01$ level.

As with the previous unimodal TS study, the exclusion criterion was based on group-level performance to determine what the level of acceptable performance is when including ~95% of the participants. Group-level performance was at 70% accuracy so that, in our sample, 95.04% of participants reached this level of performance (Mean accuracy=89.63%, SD=11.91%). This cumulative probability method allows us to exclude participants with extreme performance while also letting the sample determine what the representative level of performance is. This resulted in the exclusion of 5 4-year-olds, leaving data from 29 four-year-olds (Male=13), 25 six-year-olds (Male=16), and 26 adults (Male=9) for the analyses.

3.3.1 Overall Accuracy and Reaction Time (RT)

3.3.1.1 Group Effects (Age, Gender and Target Set)

To test for group effects, between-subject factors of Gender, Target Set (set 1: bird-dog; set 2: cat-sheep), and Age were entered into a multivariate analyses of variance (MANOVA) on RT and Accuracy. There were no significant interactions among the variables (Fs<2.45, ps>.090), and no significant effect of Gender on either dependent measure (F(1,68)<.20, ps>.600). There was no significant effect of Target Set on RT (F(1,68)=3.0, p>.080) or Accuracy (F(1,68)=.11, p>.700). There was a significant effect of Age on RT (F(2,68)=79.43 p<.001) and Accuracy F(2,68)=49.78 p<.001). As expected, older participants were both more accurate and faster than younger participants (4-year-olds: Mean(SE)=83.9(1.4)%, 1632(52)ms; 6-year-olds: Mean(SE)=94.5(0.6)%, 1170(43)ms; adults: Mean(SE)=98.1(0.4)%, 848(40)ms).

3.3.2 Task-associated costs

3.3.2.1 Mixing Cost

Task-associated mixing costs were determined by comparing the performance between trials in the pure blocks, and repetition trials in the mixed blocks. Since task cues were presented every four trials in both pure and mixed blocks, to control for the cueing effect, only trials not preceded by the task cue were analysed. The number of RT data samples obtained in the pure blocks was Mean(SD)=20.6(3.0), and for the mixed blocks was Mean(SD)=44.6(4.8). The mean Accuracy and RT on pure trials and mixed trials (i.e. repetition) did not reveal any consistent mixing effect in any age groups (Fig. 3.2).

A mixed model ANOVA was carried out with Block Type (pure vs. mixed-repetition) as a within-subject factor, and Age as between-subject factor, on the dependent measures of RT and Accuracy. There were no significant effects of Block Type on either RT or Accuracy (ps>.500); nor interactions between Age and Block Type on Accuracy (p>.800), although there was a trend on RT (*p*=.068). The marginal interaction between Age and Block Type in RT appeared to be driven by the longer RT in the mixed blocks in 6-year-olds; however, no overall mixing effect on RT was found across the age groups.

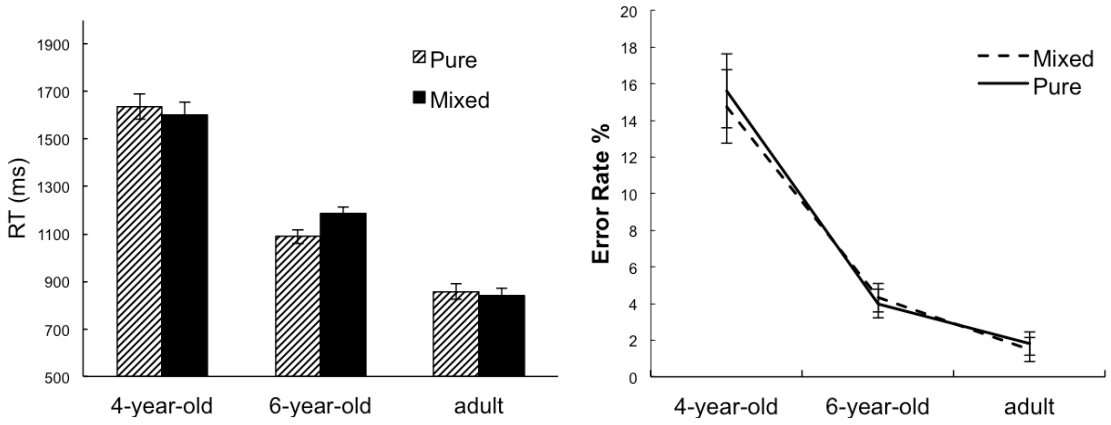

Figure 3.2. Mixing Cost: Reaction time (left-panel) and error rates (right-panel) in the Pure blocks and the Mixed blocks (i.e. repetition trials) in different age groups. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

3.3.2.2 Switch Cost

The accuracy switch cost was calculated by comparing the repetition trials and switch trials in the mixed blocks (see Figure 3.3). The RT switch cost was calculated by comparing the modality-shift task-repetition trials (MSTR) and switch trials in the mixed blocks (due to the intermittent task cue, modality shift/repetition cannot be indexed on switch trials). Comparing switch trials with

MSTR trials allowed within-modal priming facilitation on repetition trials to be controlled for. The results were analysed with a mixed model ANOVA with Trial Type (repetition vs. switch) as the within-subject variable, and Age as the between-subject variable, on dependent measures of RT and Accuracy. The number of RT data samples obtained for switch trials was Mean (SD)=13.9(1.8), and for repetition trials was Mean (SD)=8.9(1.6).

There was a significant main effect of Trial Type on RT ($F(1,77)=5.34$, $p=.024$, $\eta^2=.0.65$), but no interaction between Age and Trial Type on RT ($p>.100$). Figure 3.3 shows that RT was longer on switch trials than on repetition trials, indicating a reliable switch cost in RT.

There was also a significant main effect of Trial Type on Accuracy ($F(1,77)=31.70$, $p<.001$, $\eta^2=.293$), and an interaction with Age ($F(2,77)=4.756$, $p<.011$, $\eta^2=.110$). The interaction between Trial Type and Age on Accuracy was followed up with repeated ANOVA tests separated by age groups. The result of this analysis revealed a significant effect of Trial Type in 4-year-olds ($F(1,28)=6.37$, $p=.018$, $\eta^2=.185$), a much larger effect in 6-year-olds ($F(1,24)=30.67$, $p<.001$, $\eta^2=.561$), but no significant effect in adults ($F(1,25)=3.16$, $p=.087$, $\eta^2=.112$). However, descriptive statistics show that all ages exhibit a trend for a larger error rate on switch trials than repetition trials (Fig. 3.3).

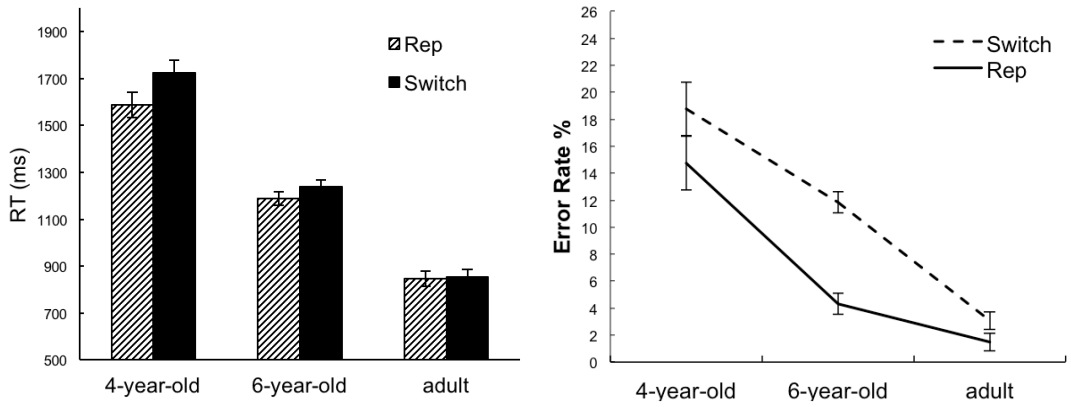

Figure 3.3. Switch Cost: Reaction time (left-panel) and error rates (right-panel) on Repetition trials and Switch trials in different age groups. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

3.3.2.3 Response priming effects (RR)

The *response priming effects* were explored with *stimulus-led* primed trials (vs. unprimed trials) in pure and repetition trials, and *response-led* primed trials (vs. unprimed trials) in switch trials. In pure and repetition trials, a trial was considered primed if the target stimuli on two consecutive trials were both (1) associated with a correct button-press (thus a repeated-response), (2) of the same category but not necessarily of the same value (e.g. the same picture), and (3) of the same modality. In switch trials, it was not possible to define primes in the same way since the previously responded-to target would be a nontarget, and therefore most likely a nonresponse on switch trial (i.e. no RT recording). Instead, a primed switch trial simply refers to any correct response preceded by another correct response (both involving button-press), regardless of whether there was a stimulus repetition. With these definitions in mind, there are two types of trials—a *primed response* trial and an *unprimed response* trial. Our behavioural result shows that this response priming has an RT facilitative

effect in pure and repetition trials, and a lack of facilitation or a cost in switch trials (Fig. 3.4). The direction of the effects is consistent to past literature.

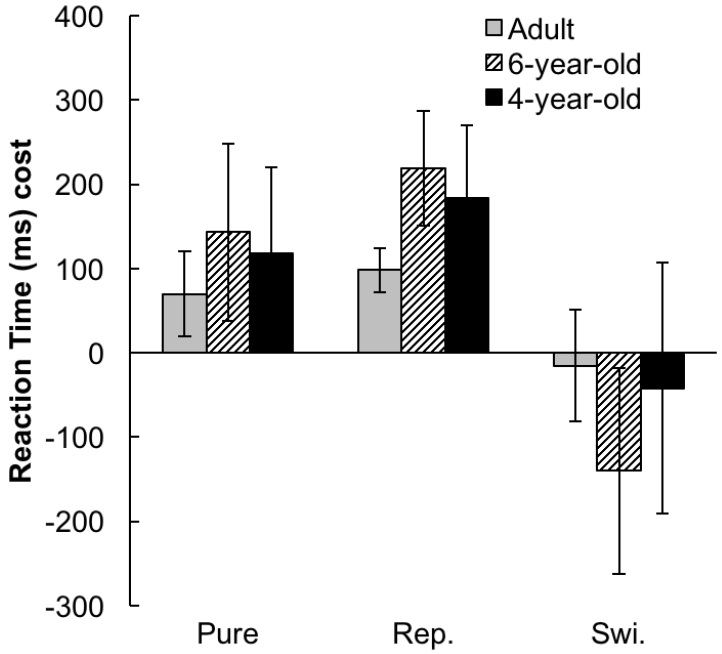

Figure 3.4. Response priming (RP) effect on different trial types in bimodal CMTS behavioural experiment. On pure and repetition trials, the RP effect was stimulus-led (RT differences between unprimed single-response trials and primed repeated-response trials with the same stimulus category-modality); on switch trials, the RP effect was response-led (RT differences between single-response vs. repeated-response). Positive values indicate RP facilitation and negative values indicate RP cost. Error bar indicates 95% CI.

The results were analysed with a mixed ANOVA with Trial Type (3 levels: pure, repetition and switch trials) and Response Prime (primed response vs. unprimed response) as the within-subject variable, and Age as the between-subject variable, on dependent measure of RT. The main focus here was the effect of Response Prime, which was significant ($F(1,77)=16$, $p<.001$, $\eta^2=.172$). There was also a significant interaction between Response Prime (RP) and

Trial Type ($F(2,154)=20.58$, $p<.001$, $\eta^2=.211$). No further interactions with Response Prime were found ($Fs<1.9$, $ps>.100$).

The interaction between Response Prime and Trial Type was further explored by analysing the effect of Response Prime in different trial types with multiple paired t-tests (Bonferroni corrected to alpha=.017. There was a significant RP facilitation in pure trials ($t(79)=4.16$, $p<.001$, one-tailed), and in repetition trials ($t(79)=8.22$, $p<.001$, one-tailed). There was no significant RP cost in switch trial ($t(79)=1.80$, $p=.037$, one-tailed). The overall result is consistent to past literature on task-switching which found facilitative effect of response prime is confined to within-task but not between-task.

3.3.3 Modality-associated effects

3.3.3.1 Target Modality

Target modality denotes which modality the task-relevant target was presented in. In the pure blocks, the mean number of data samples for visual target was Mean(SD)=15.4(2.2), and for auditory target was Mean(SD)=13.2(2.6). In the mixed blocks, the mean number of data samples for visual and auditory were Mean(SD)=25.5(2.3) and Mean(SD)=24.8(3.7), respectively. Overall, the participants were quicker to visual than auditory targets in both pure and mixed blocks (Fig. 3.5 and Fig. 3.6), with the exception of 4-year-olds who exhibited similar RTs to either target modalities in the pure blocks. The children achieved higher accuracy to visual targets than to auditory targets, particularly in the mixed blocks. The Adults showed comparable accuracies to either visual or auditory targets.

A three-way mixed ANOVA with Age as a between-subject factor and, Target Modality and Block Type (pure and mixed) as within-subject factors was

carried out on accuracy and RT. There were a significant overall main effects of Target Modality on RT ($F(1, 77)=32.31$, $p<.001$, $\eta^2=.296$), and Accuracy ($F(1, 77)=7.08$, $p=.009$, $\eta^2=.084$). However, these were modulated by a three-way interaction on RT ($F(2, 77)=5.762$, $p=.005$, $\eta^2=.130$), but not on Accuracy ($p>.800$).

The three-way interaction on RT was followed up with repeated ANOVAs with Target Modality and Block Type as factors, separated by age groups. The main effect of Target Modality remained across all age groups ($Fs>7.90$, $ps<.010$) in the follow-up analyses. The interaction between Target Modality and Block Type was significant in both 4-year-olds ($F(1, 28)=10.01$, $p=.004$, $\eta^2=.263$) and 6-year-olds ($F(1, 24)=4.81$, $p=.038$, $\eta^2=.167$), but not in adults ($p>.600$). This result suggests that the quicker response to visual targets than auditory targets was stronger in the mixed blocks than in the pure blocks among young children.

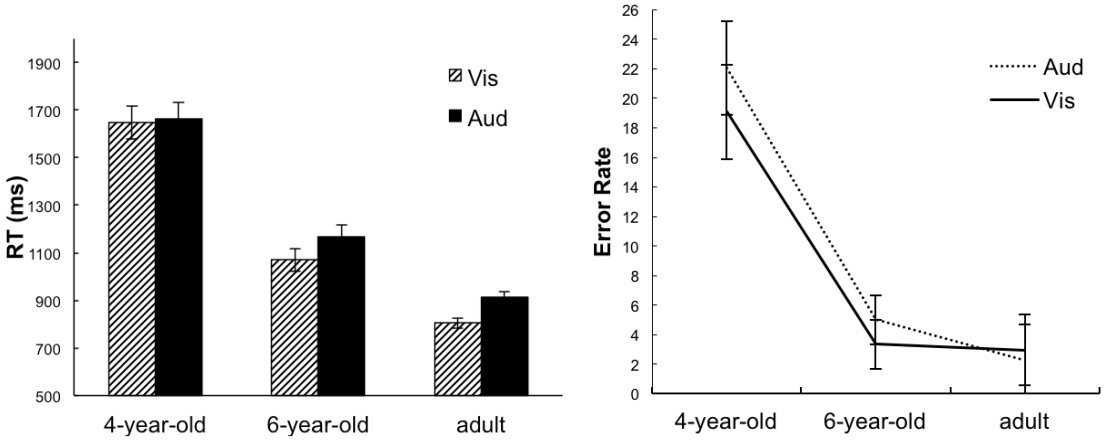

Figure 3.5. Mean RT (left panel) and Accuracy (right panel) to visual and auditory targets in the pure blocks. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

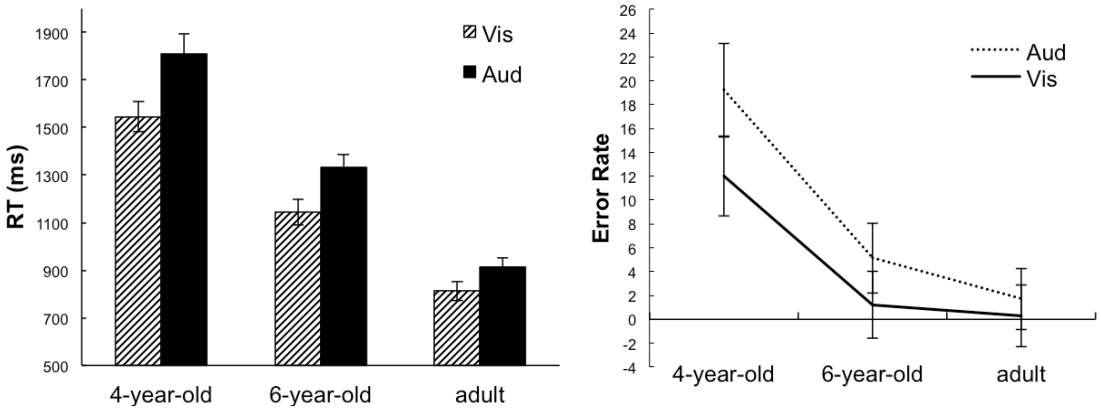

Figure 3.6. Mean RT (left panel) and Accuracy (right panel) to visual and auditory targets in the Mixed blocks. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

3.3.3.2 Modality Shift Effect

The Modality Shift Effect (MSE) is the cost of shifting attention to another modality, compared to attending to the same modality. To analyse the MSE, trials with a target appearing in the same modality as in the n-1 trial were compared with trials with a target of a different modality from the n-1 trial. For example, on trials with visual targets, the MSE is the RT difference between a visual-to-visual trial (V2V, where the previous target also contained a visual target) and an auditory-to-visual trial (A2V, where the previous trial contained an auditory target). Only trials not immediately proceeded by the task cues (i.e. pure and repetition trials) were analysed since the intervening task cue prevented the inter-trial index from being calculated. Furthermore, only consecutively correct responses were analysed (i.e. both the n-1 trial and the current trial were both correct positive responses). This means that only RT were analysed since the main interest here is on the act of attentional shift (i.e. information is attended to), but not on the failures to attend. One 4-year-old, two

6-year-olds, and one adult did not have any RT data for one of the trial types and were thus excluded from the analyses. The mean number of data samples is shown in Table 3.1. Results are shown in Figure 3.7.

Table 3.1. Number of data samples for each trial type.

	Pure		Mixed	
	Repetition	Shift	Repetition	Shift
Visual	3.9(1.0)	2.1(0.9)	6.5(0.9)	5.9(1.0)
Auditory	4.3(1.1)	4.7(1.5)	6.2(1.2)	3.0(0.9)

Note: number denotes mean and standard deviation in parentheses.

A four-way mixed ANOVA was conducted with Target Modality (Visual vs. Auditory), Modality Transition (modality-shift vs. modality-repetition) and Block Type (Pure vs. Mixed) as within-subject variables, and Age as a between-subject variable. The main interest here is the effect of Modality Transition and its interaction with other variables.

The main effect of Modality Transition was significant ($F(1,73)= 22.25$, $p<.001$, $\eta^2=.234$). However, there was also a significant three-way interaction among Target Modality, Modality Transition and Block Type. The interaction was caused by a reversal in the MSE in the pure and mixed blocks (Figure 3.6). In the pure blocks, the MSE cost to auditory targets (V2A-A2A) was reliably larger than zero, but the MSE cost to visual targets (A2V-V2V) was not reliably different from zero. This pattern was reversed in the mixed blocks, in which the MSE cost was reliable on trials with visual targets but not auditory targets. There was no further interaction between Modality Transition and other variables ($ps>.100$).

Although the data samples were relatively sparse for the analysis of the MSE, the result nevertheless showed a clear pattern of interaction between MSE and Block Type, which was consistent across age groups. Although the modality shift cost in RT was significant in all conditions, the *direction* of the MSE was dependent on the task condition.

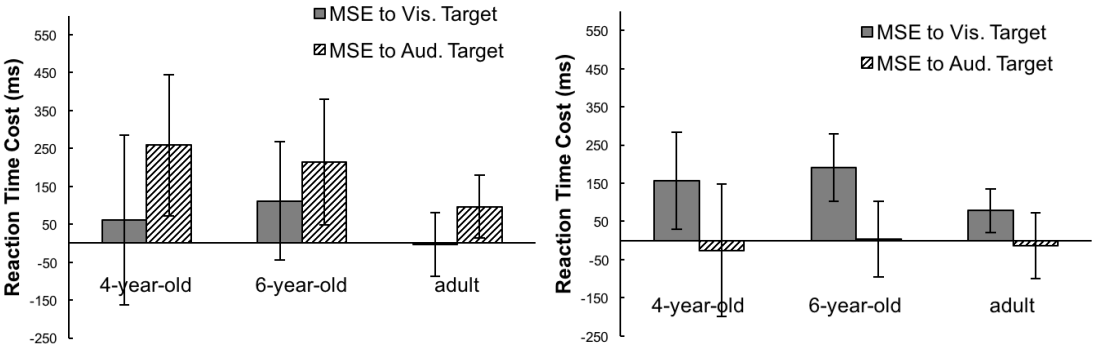

Figure 3.7. MSE in RT to visual target (A2V-V2V) and to auditory target (V2A-A2A), in either pure blocks or mixed blocks. Bold letters denote the target modality. Error bars represent 95% CI of means.

3.3.4 Modality dominance effect

3.3.4.1 Baseline Analyses

Eleven 4-year-olds, 11 6-year-olds and 10 adults completed the baseline condition. One 4-year-old was excluded from this analysis due to their low accuracy scores in the main experiment, leaving 10 4-year-olds in the final analysis. All ages achieved high accuracy (4-year-old: Mean(SE)=94.8(1.4)%; 6-year-old: Mean(SE)=98.8(0.4)%; Adult: Mean(SE)=99.8(0.2)%). As expected, younger children were still slower than older participants (4-year-old: Mean(SE)=1299(87) ms; 6-year-old: Mean(SE)=896(75)ms; Adult: Mean(SE)=630(64)ms).

3.3.4.2 Cross-modal distractor effect

The cross-modal distractor effect was examined by comparing RTs on unimodal baseline trials with bimodal trials in the pure blocks (see Figure 3.8). As discussed above, the cross-modal distractor effect was used to investigate modality dominance. A larger distractor effect of a visual distractor on an auditory target than of an auditory distractor on a visual target would imply visual dominance.

To examine the cross-modal distractor effect, a mixed ANOVA was carried out with Target Modality (visual vs. auditory) and Condition (baseline vs. pure) entered as within-subject variables, and Age as the between-subject variable on dependent measure of RT. Accuracy was not examined due to the ceiling performance in the baseline condition. There was a significant main effect of Target Modality ($F(1,28)=48.63$, $p<.001$, $\eta^2=.635$), but no interaction with Age. ($p>.700$); all ages were quicker at responding to visual targets than auditory targets in either baseline or pure blocks (Fig. 3.7). There was also a significant main effect of Condition ($F(1,28)=30.50$, $p<.001$, $\eta^2=.521$); RTs were longer in the pure blocks with cross-modal distractors than in the baseline condition.

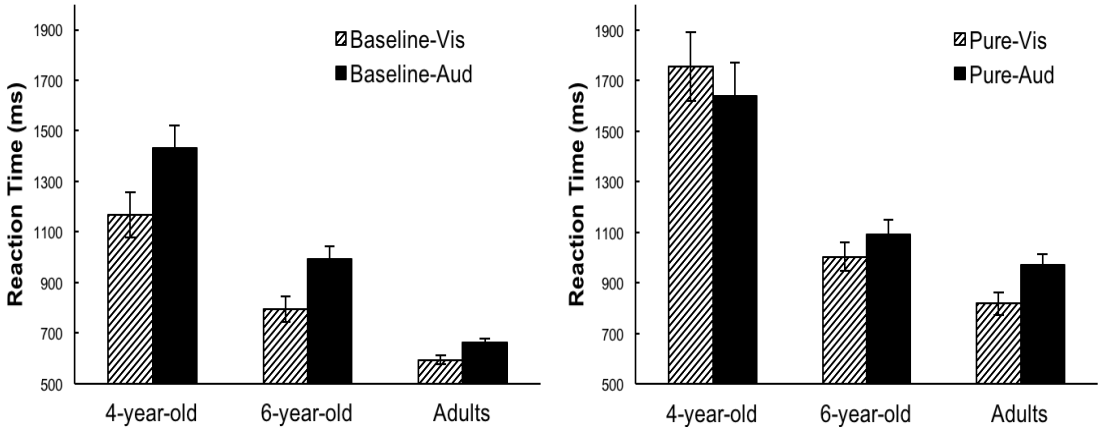

Figure 3.8. Reaction time to targets in different modalities (visual vs. auditory targets) in different age groups. Left-panel: baseline unimodal condition; right-panel: pure blocks with cross-modal distractors. All error bars denote within-subject 95% confidence intervals of means (Cousineau, 2005).

The modality dominance effect was explored using RT differences between unimodal trials and bimodal trials. Figure 3.9 shows the RT differences between baseline and pure trials by distractor modalities in different age groups. The cross-modal auditory distractor effect decreased with age, whereas the cross-modal visual distractor effects appeared to increase with age. This transitional pattern from auditory dominance to visual dominance with development is in agreement with past literature.

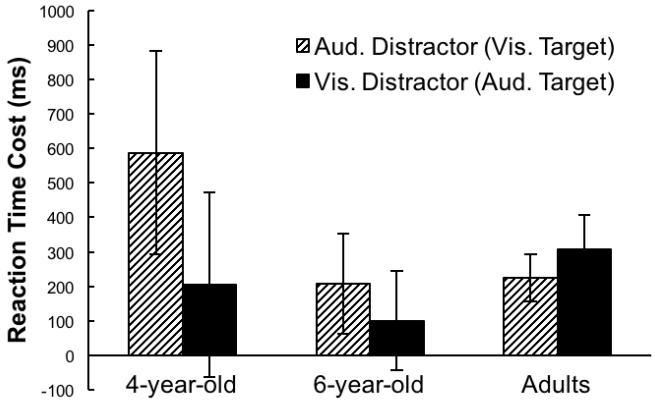

Figure 3.9. Cross-modal distractor effect in RT costs to visual targets and to auditory targets. The cost was calculated as the differences between bimodal pure trials and unimodal baseline trials. Error bars represent 95% CI of means.

The age differences in modality dominance was supported by the three-way interaction among Target Modality, Condition and Age ($F(2,28)=5.85$, $p<.010$, $\eta^2=.295$). The interaction was followed up with two-way repeated ANOVAs with Target Modality and Condition, separated by age groups. Only adults showed a significant two-way interaction between Target Modality and Condition, indicating asymmetric costs between cross-modal auditory and visual distractors (to their respective visual and auditory targets). The mean RT costs point to visual dominance in adults. Although children did not exhibit significant differences between cross-modal auditory and visual distractors, the mean RT costs with 4-year-olds did exhibit a trend with a larger auditory distractor cost than visual distractor cost ($F(1,9)=3.882$, $p=.080$, $\eta^2=.301$), indicating an auditory dominance. The non-significant difference was likely due to a lack of power since the sample size in the baseline condition was small. In comparison, 6-year-old did not exhibit any asymmetric cost between auditory and visual cross-modal distractors ($F(1,9)=.417$, $p>.500$, $\eta^2=.040$).

In sum, although the baseline condition was carried out with a limited number of participants, the overall result supports the idea of a shift from auditory to visual dominance across development.

3.4. Discussion

The current study started with a simple desire to understand whether task-associated mixing costs and switch costs are invariant across unisensory and multisensory contexts. If multi-task management and switching between tasks both rely mainly on supramodal goal representations, then experimental changes that primarily affect perceptual processes should have a limited effect on task-associated costs.

In general, no mixing effect was found in the current study, since both RT and accuracy were comparable in pure and mixed blocks. However, there was a greater RT mixing cost in 6-year-olds. This result stands in contrasts to the results in the unimodal TS study (Chapter 2), where we found both significant accuracy and RT mixing costs across all ages. This is surprising since the mixing costs in task-switching studies are normally more robust than switch costs. To our knowledge, none of the existing studies that included pure blocks reported an absence of mixing cost (e.g. Los, 1996; Poljac, Koch, & Bekkering, 2009; Rogers & Monsell, 1995; Rubin & Meiran, 2005; Tarantino, Mazzonetto, & Vallesi, 2016; Wylie, Murray, Javitt, & Foxe, 2009).

Two possible accounts may explain the lack of mixing effect reported here. The first relates to multisensory attention to bimodal stimulus, and the second relates to task structures in pure and mixed blocks. According to the first explanation, it is possible that between-task interference is smaller when the supramodal task goal is not strongly tied to a specific modality. In this case, the

selection demand is smaller with multisensory input since visual and auditory processing can be carried out in parallel. Under this scenario, mixing costs may largely reflect the differences in lower-level stimulus-response selection, rather than the difference in active goal representations between pure and mixed blocks.

An alternative account is that pure and mixed task conditions are not necessarily comparable. Indeed, the similarities and differences between tasks in the pure and mixed blocks have never been properly addressed. Most theories of mixing cost have focused on the representational ambiguity caused by task set overlaps in the mixed blocks. They are therefore implicitly based on the assumption that the task structures in the pure and mixed blocks are comparable. This assumption may be premature since it is entirely possible to carry out pure tasks with simple stimulus-response associations and without forming an overarching task goal (e.g. *colour* task). Participants may be more motivated to construct a task set with a supramodal task goal, where possible, when information interference is consciously perceived. This motivation may occur more naturally in the mixed blocks than the pure blocks.

Without a strong representation of a common task goal, responses to the stimulus may be relatively unprepared, as attention may be less finely tuned to the relevant stimulus attribute. Evidence in support of this comes from Forrest, Elchlepp, Monsell and McLaren (2012) who investigated performance when responses were made purely by learning cue-stimulus-response (CSR) associations, or through a higher order task structure (magnitude vs. parity judgment on digital numbers). All stimuli and trial sequence were identical in both CSR and Task conditions, so the critical difference between the conditions was the internal representations of task structures. Both reaction time and error

rates were higher on CSR trials than on task-repetition trials, and highest on task-switch trials. These results indicate that between-condition comparison is dependent on how the tasks are structured, and how information compounds are formed in the first place. In the pure blocks, a strong goal representation may facilitate performance but is not necessary for accurate performance. In comparison, active goal settings often necessary in the mixed blocks. When active goal-setting is not present, the reaction time and the accuracy in the pure blocks may be compromised, thus reducing the between-condition mixing effects.

At the moment, it remains unclear whether the lack of mixing effects found in 4-year-olds and adults was due to multisensory attention factors, differences in task structures, or both. Nor is it clear why only 6-year-olds exhibited RT mixing costs. Although the underlying mechanisms are unclear, the current result suggest that mixing effects are not a universal phenomenon, and point to the need to have a clearer understanding of the pure task condition. This need is perhaps more pertinent in developmental research, where young children may not intuitively construct complex task rules, despite having the ability to do so.

In comparison, both RT and accuracy switch costs were significant in the current study, even after controlling for possible perceptual-based facilitations on repetition trials. This result indicates that switching between tasks is distinct from shifting between modalities. Although the RT switch effect was evident in the current study, it did not interact with age. This finding is consistent with the unimodal TS experiment (Chapter 2) and continues to suggest that young children are adept at switching between tasks with familiar stimuli and that they can actively form supramodal task goals. However, the accuracy switch cost

was larger in 6-year-olds than in other age groups. It is remains unclear why 6-year-olds showed larger mixing cost and switch cost than other age groups.

Although between-condition effects were by-and-large similar in different age groups, the overall response time and error rates were still larger in younger children than adults, particularly 4-year-olds. What may explain the discrepancies between the within-subject measures and between-group measures? One possible explanation is that although young children were able to construct task representations appropriately (at least in the mixed blocks), and exhibit the ability to change behaviours according to task instructions, certain developmental constraints prevent them from performing to a high consistency. It is not clear if these constraints are associated with domain-general endogenous control—such as inhibitory control and working memory, global development that underpins simple processing speed, or both.

Our experiment also replicated the result that priming facilitation is constrained by task repetition, as the facilitative effect from response prime was observed only in pure and repetition trials, but not in switch trials. Although due to experimental procedure we could not index stimulus-led primes in switch trials, our results are in agreement to past research which shows that primed components, such as a repeated response and a repeated stimulus, are facilitative only when the task repeats but not when the task switches.

With regards to modality dominance, the current study found a trend for auditory dominance in 4-year-olds and evidence of visual dominance in adults, with transitional non-dominance in 6-year-olds. Despite the limited number of participants, the direction of modality dominance is in line with past studies. The present study differed from past studies by focussing on RT measures rather than error-types.

Although different ages are likely to exhibit different patterns of modality dominance, the Modality Shift Effect (MSE) did not exhibit age-dependent patterns of asymmetric costs. In the pure blocks, all ages exhibited a reliable MSE to auditory targets, but not to visual targets. In other words, reorienting attention to visual targets in the pure blocks appears to be relatively easy, since no attentional shift cost in RT was observed. This is not surprising in 6-year-olds and adults since responses to visual targets were overall quicker than to auditory targets in both baseline and pure blocks, indicating an overall bias to visual processing. However, the result is somewhat surprising in 4-year-olds since they showed auditory dominance and comparable RTs to visual and auditory targets in the pure blocks. A more likely account for the result in 4-year-olds is that the MSE to visual target was overshadowed by the effect of auditory dominance in 4-year-olds, since RTs on both V2V and A2V might be elevated due to auditory distractor effects. Further research is needed to understand how MSE can be larger to the dominant modality than to the non-dominant modality in pure blocks.

In 6-year-olds and adults, the quicker overall visual processes are likely to be due to multiple factors that facilitate visual detection. In the present studies (with semantically meaningful stimuli), visual inputs are less likely to rely on temporal processing than auditory inputs. As a consequence, the identification of visual elements is likely to be quicker than auditory elements. In addition to the possible speedier perceptual processing of visual input, stimulus-response associations are likely to be stronger with visual targets, since visual-manual mappings have been found to be more compatible than auditory-manual mapping (Stephan & Koch, 2010). Lastly, the presence of a redundant auditory cross-modal distractor may enhance the perception of visual stimulus,

at least in adults. For example, Sinnett et al. (2008) reported a shorter RT to the visual element in an object-based bimodal stimulus (e.g. cat *meow* paired with a traffic light picture), than to the unimodal visual stimulus. Unlike Sinnett et al.'s study, the current study did not find a shorter RT to visual targets with bimodal stimulus than unimodal baseline stimulus, and this is likely to be due to different experimental procedures. The difference between our study and Sinnett et al.'s experiment, is that the participants in this latter study only needed to monitor one modality, compared to bimodal monitoring required in the current study. Nonetheless, it remains possible that the redundant auditory distractor has different effects on adults and children—in adults, cross-modal auditory distractor might enhance visual processes; in young children, cross-modal auditory distractor might interfere visual processing.

Thus, the lack of MSE to visual targets in the pure blocks in 6-year-olds and adults may be largely due to the favourable visual processes; whereas in 4-year-olds the lack of MSE to visual target may be more attributable to a large auditory distractor effect overshadowing the MSE. Future studies are needed to see whether the MSE asymmetry would persist with unimodal stimuli.

Surprisingly a reversed asymmetry was found in the mixed blocks—a reliable MSE to visual targets but not auditory targets. It is not clear what mechanisms underlie this reversal of the MSE asymmetry. One possibility is that modality-associated processes interacted with verbal task rehearsal in the mixed blocks. Although not explicitly documented, 4-year-olds often engaged in verbal self-instruction in the mixed blocks during the experiment. Although many fewer 6-year-olds and no adults engaged in explicit verbalisation of task rules in the mixed blocks, they might still have updated task goals with inner speech. Indeed, many studies have documented the role of verbalisation/inner speech

as a form of self-cuing in both adults and children. The disruption of verbalisation impaired performance in all ages, although the effect was larger for children and older adults than young adults (Emerson & Miyake, 2003; Karbach & Kray, 2009; Kray et al., 2008; Kray, Eber, & Lindenberger, 2004). It remains to be determined whether inner speech underlies the reversal of MSE.

Even if inner speech does interact with modality-associated processes, how this interaction eliminates MSE to auditory targets and increased MSE to visual targets in the mixed condition is far from clear. For example, the elimination of MSE to auditory targets could be accomplished in two ways—by increasing the baseline RT on modality-repetition trials, or by decreasing the RT on modality-shift trials. Similarly, the increase of MSE to visual targets could be achieved either by decreasing the baseline RT on modality-repetition trials, or by increasing the RT on modality-shift trials. Further research is needed to understand the mechanisms underlying the reversal of MSE in the mixed blocks.

3.5 Conclusion

The present study reports the first cross-modal task-switching study in developmental research that we are aware of. Past developmental studies have often report mixed findings in terms of the age effects on mixing cost and switch cost in unimodal contexts. This is consistent with our finding of a lack of age interaction effect on either costs in the present study. Although both unimodal TS and bimodal CMTS studies demonstrate that children as young as 4 years of age are equipped with a general ability to switch between tasks, age differences in absolute accuracy and RT remained. The overall result thus questions whether task-associated endogenous control can be measured with

mixing cost and switch cost. Further behavioural studies and perhaps other research methods such as computational modelling may shed lights on the relations among global development and/or endogenous control, between-condition and between-trial costs, and the overall performance measures.

While task-associated switch costs appear robust in either unisensory and multisensory environment, in comparison, modality shift effects are dependent on task contexts. The MSE in the pure blocks and mixed blocks had different directions of asymmetry. Although different modality dominances were found in different age groups, the current study was unable to ascertain how modality dominance may interact with MSE, due to several confounding effects. Because MSE is an inter-trial effect, it is not clear whether the lack of MSE to visual targets in the pure blocks was due to the multiple facilitators on visual processes that override the MSE, as previous adult research would suggest, or, whether it was due to the overshadowing effect of auditory dominance in children that elevated the RTs to visual targets. It is possible that different ages experienced different facilitation/interference effects in visual processing during the pure blocks.

The most striking finding is the reversal of MSE in the mixed blocks. It is not clear what specific task demands in the mixed blocks interacted with the MSE, but one plausible candidate is the role of inner speech. However, the underlying mechanisms are unclear at this stage.

Both task-associated effects and modality-associated effects are likely to come from complex interactions among different information processes. Potentially, modality-associated effects are even more dynamic than task-associated effects, since they can emerge at different level of processes (e.g. encoding speed, stimulus-response compatibility, modality dominance, inner

speech and so on). It may be particularly difficult to understand how modality-specific processes and task-associated processes interact through behavioural research method alone. There is also an additional challenge in understanding these interactions in a developmental context. Thus, instead of carrying out a long series of developmental experiments investigating the interactivity of multiple processes, the present thesis turned to computational modelling as a way to understand how these task-associated effects and modality-associated effects emerge in dynamic connectionist networks. The details and results of the computational models for bimodal CMTS study are reported in Chapters 5 to 8.

In the next chapter, we will explore task switch effects and modality shift effects using unimodal stimuli. The experiment in Chapter 4 involves a different experimental procedure, as well as different tasks and stimuli, and the purpose of these changes is to understand the generalisability of our findings so far. Specifically, the study in Chapter 4 was designed to be more challenging than the studies so far, as in the next study both task and modality changed unpredictably with no forewarning from a pre-cue. The main objective of the study in Chapter 4 is to examine the interaction between task transition (repetition and switch) and modality transition (repetition and shift), in order to understand the similarity and differences in these two forms of attentional shifts, and to appreciate how amodal the overall task sets are.

Chapter 4. Experiment 3: Cross-modal task-switching with unimodal stimuli (unimodal CMTS)

The unimodal TS and bimodal CMTS studies in Chapter 2 and 3 respectively have examined whether younger children experienced greater difficulty in switching task goals than adults. Our experiments did not uncover a consistent age interaction effect on switch costs and thus, so far, argue that young children and adults experience a comparable level of difficulty in repeatedly switching between tasks. That said, younger children were still overall slower and less accurate on all trial types. So even if task switching bears no additional cost compared to adults, their baseline level of performance is lower than that of adults. This absence of an age interaction effect on switch cost could potentially be explained by factors that facilitated task preparation in the previous studies—(i) a long preparation window, (ii) addition task cues on switch trials, (iii) fixed trial sequence, and (iv) perceptually-based target categories. It then follows that eliminating these favourable factors may reveal age modulated differences in switch costs. In this chapter, with a suitable modifications of the experimental procedure to remove these possible facilitative factors, we will focus on the effect of switching between task goals and shifting between modalities with unimodal stimuli.

In the bimodal CMTS study, we did not find a larger modality shift costs (MSE) in children, as compared to adults. However, the MSE measure in the bimodal CMTS study could have been affected by modality dominances thereby obscuring the true cost of inter-trial modality shifts. Additionally, the MSE was not measured on task-switch trials, due to the limitation arising from the experimental procedures. Since the modality dominance effect refers to

concurrent cross-modal interference from the dominant modality, the dominance effect can be supressed by using unimodal stimuli.

4.1 Introduction

The differentiation of perceptual systems and the emergence of multisensory systems undergo rapid changes in the first 2 years of life (Bremner et al., 2012; Lewkowicz & Ghazanfar, 2009), yet different forms of cross-modal interaction, such as integration, overshadowing (e.g. modality dominance), facilitation, distraction and learning, continue to develop throughout childhood (e.g. Brandwein et al., 2011; Broadbent, White, Mareschal, & Kirkham, 2017; Matusz et al., 2015; Nardini, Bales, & Mareschal, 2016; Nava & Pavani, 2013; Sloutsky & Napolitano, 2003; Thomas, Nardini, & Mareschal, 2017). These cross-modal effects can exhibit large task-dependent heterogeneity, often in the form of age-dependent asymmetric costs or facilitations. Collectively, these studies suggest that cross-modal interactions may happen on many levels of processing, although it is much less clear whether all of the processes involved are modality dependent, or, simply task dependent.

To address these questions, the present study aims to understand how amodal the task sets are when the task goals are defined with supramodal properties. In addition, the study explores any developmental differences in information processing during cross-modal task-switching that might exist between young children and adults. In what follows, we first look at the limited research on cross-modal task-switching in the adult literature, then give a brief overview of the research into attentional flexibility and cross-modal interaction in developmental literature, before outlining our study and hypotheses.

4.1.1 Cross-modal processes in adult task switching

Early studies using dual visual and auditory detection tasks suggested that visual and auditory processing are largely distinct (Duncan, Martens, & Ward, 1997). However, shifting attention to another modality results in reliable RT costs (Sutton, Hakerem, Zubin, & Portnoy, 1961), implying that cross-modal attentional shifts tap into a common processing resource shared between modalities. An alternative explanation is that this modality shift cost is largely attributable to task-switching costs (Soto-Faraco & Spence, 2002), since when the participants shift attention cross-modally, they also attended to an alternative target. One critical question, therefore, is whether the presentation modality is just another task attribute like colour and shapes in unisensory task-switching experiments. One way to test this idea is to look at the interaction between different types of attentional transitions (modality vs. task) and response transitions. Past research on task-switching has reported that response repetition is facilitative only when the task repeats, but not when the task switches (Rogers & Monsell, 1995). Indeed, Cohen and Rist (Cohen & Rist, 1992) found that modality shift effect was only evident when a response was executed previously. However, without a well-defined task that bridge across the auditory and visual stimuli, any modality associated effect observed may be contaminated with task associated effects.

To date, there have only been a handful of cross-modal task-switching studies in which both visual and auditory stimuli shared the same task attribute (Hunt & Kingstone, 2004; Murray et al., 2009; Sandhu & Dyson, 2013). As with the usual unisensory task-switching procedure, Hunt and Kingston (Hunt & Kingstone, 2004) asked participants to switch between two simple number choice tasks (odd/even vs. large/small) where the stimulus could be either

visual or auditory. They found that task-switching and modality-shifting each produced reliable RT costs. While the reaction time on the trials requiring a simultaneous modality and task change (modality-shift task-switch trials, or MSTS) was the longest, the observed cost was less than the combined task-switching and modality-shifting costs when added together individually. In other words, a *subadditive effect* to the combined costs was observed. One explanation for this finding is that modality-shifting and task-switching are both independent but also interdependent, subjected to a common processing bottleneck yet facilitated through separable pathways. In contrast, Murray et al. (Murray et al., 2009) found a stronger *facilitative* effect of modality-shifting on task-switching, as RT on MSTS was faster than on trials with task-switch alone (i.e. with modality repetition). Their experiment involved where/what classifications on either man-made or natural objects/sounds. They explained the result through both interference and an episodic binding effect between task and modality, such that when one index changes (e.g. modality), there is a relative advantage when the task changes as well due to relatively reduced interference in the network.

Both Hunt and Kingston and Murray et al. employed unimodal stimuli in their studies, but a similar effect can also be found with bimodal stimuli. For example, Sandhu and Dyson (Sandhu & Dyson, 2013) employed different cueing methods in their study (no-cue, single-cue to either modality or task, and dual-cue to both modality and task) and found a general subadditive effect on trials with simultaneous modality and task change, although the effect was not as large as that reported in Murray et al.'s study (Murray et al., 2009). They also found some differences between modality-shifting and task-switching. Modality shift costs in RT were only evident in the no-cue condition, whereas task switch

costs in RT were reliable in both no-cue and single-cue conditions. Thus, it appears that task representations are more complex and only when full information is provided would the processing costs be effectively eliminated. The result suggested that task-switching and modality-shifting may engage different attentional operations, and that modality-shifting appears to be less cognitively taxing than task-switching. However, in both cases, RT costs were eliminated when both modality and task cues were provided.

In contrast to the results from cross-modal task-switching studies, a complete elimination of processing costs in unisensory task-switching experiments was rarely reported, even with univalent stimuli where only one task was possible on each trial (Lien, Ruthruff, & Kuhns, 2006; Mayr, 2001; Wylie & Allport, 2000). It is therefore important to understand how simultaneous change in task and modality reduces and/or eliminates processing costs.

4.1.2 Attentional flexibility and multisensory development

As we have seen in Chapters 2 and 3, young children do not necessarily exhibit a larger shift cost during task-switching. These result suggest that children's attentional flexibility in responding to environemtal changes is relatively well developed in early childhood, although with the caveat that they are still more likely to make errors regardless of the external environment. Although young children can be as effective at switching between tasks as adults, given an age-appropriate task, they may still exhibit cross-modal task-switching effects different from those of adults due to a developing multisensory system. While there is no direct developmental research on cross-modal task-switching, children and adults show differences in brain activation patterns in cross-modal oddball detection. For example, Johannsen and Röder (Johannsen

& Röder, 2014) looked at the refractory effect of within-modal and cross-modal oddball detection tasks with unimodal stimuli (either sound or picture). They found that while young children aged between 4 and 6 showed similar overall refractory effects to within-modal target detection, compared to older children aged 10 and 12 and adults, the cross-modal refractory effect was different in the youngest group. Young children showed cross-modal refractory effects earlier in processing as compared to older participants, and the supra-modal interaction of cross-modal information was stronger in young children than older children and adults. Topographically, younger children also exhibited more activation in the frontal region, an area that is heavily implicated in cognitive control, as compared to the parietal topography found among older children and adults. The result suggests that younger children are more likely to exert endogenous influence to direct attention cross-modally, perhaps to overcome for the greater neural interference due to the less specialised (i.e. less segregated) short-range networks (Fair et al., 2009; Fair et al., 2007). If so, children may experience a greater attentional bottleneck in conditions in which cross-modal attentional shifting is required.

4.1.3 The current study

The current study is designed to explore whether processing costs in RT and accuracy associated with modality-shifting and task-switching reflect any developmental changes during early childhood. The current cross-modal task-switching study employed a simple detection task with a single response key. Using a single response key minimises the demands on response selection, and ensures that the observed response latency reflects the time needed to shift attention at the level of modality and task goal.

We make a number of predictions based on the literature reviewed above. Firstly, consistent with the previous literature, we hypothesise that both task-switching and modality-shifting will produce attentional costs, in both children and adults. Secondly, when a child-friendly procedure is used we hypothesise that young children can be as effective as adults at switching between task goals and selecting the appropriate stimulus attribute to respond on. Thirdly, we expected that children will require more endogenous control than adults in order to shift attention cross-modally. As a result, we predict that younger children will exhibit greater modality shift costs than older children and adults. Finally, if younger children require greater endogenous control to shift attention cross-modally, they will show additive costs of modality-shifting and task-switching, whereas adults will benefit from modality-shifting during task-switching, and therefore show a facilitative effect or at least subadditive costs when switching both task and modality.

4.2 Method

4.2.1 Participants

Forty-two 4-year-olds, 30 6-year-olds and 24 adults were recruited for the experiment. Seventeen 4-year-olds and 4 6-year-olds were excluded from the analyses: 5 4-year-olds and 2 6-year-olds were unable to complete the training element of the study sufficiently well, and 12 4-year-olds and 2 6-year-olds did not pass the baseline accuracy on 70% in the testing session. Consequently, a total of 25 4year-olds (Male=12, mean age=4.66 years, SD=.23 year), 26 6-year-olds (Male=17, mean age=6.57 years, SD=.27 year) and 24 adults (Male=13, mean age=27.18, SD=8.21 years) were included in the final analyses presented below.

All children were recruited from local primary and nursery schools, with the exception of nine 4-year-olds recruited separately to the testing lab at the research centre. All testing was conducted in a quiet room in the participant's school or in the lab testing room in the research centre. Children were given token rewards (i.e. stickers) at the end of each block to maintain their motivations. Each session lasted around 25 minutes. Adult participants were recruited from the University campus. No rewards were given to adults and they were tested in a quiet room of the University campus. All participants had normal or corrected to normal vision and hearing.

4.2.2 Stimuli and design

The experiment consisted with two different detection tasks: an animal detection task cued by a drawing of a barn house, and a musical instrument detection task cued by a drawing of musical notes. The targets in the animal detection task were various animal pictures and animal sounds, and the targets in the musical instrument task were various pictures of musical instrument and musical sounds. The targets could be presented in either modality and all trials were unimodal (i.e. only a sound or an image was presented). Task cue (approx. 2.2cm x 1.9cm) and the stimulus were presented simultaneously (Fig 4.1).

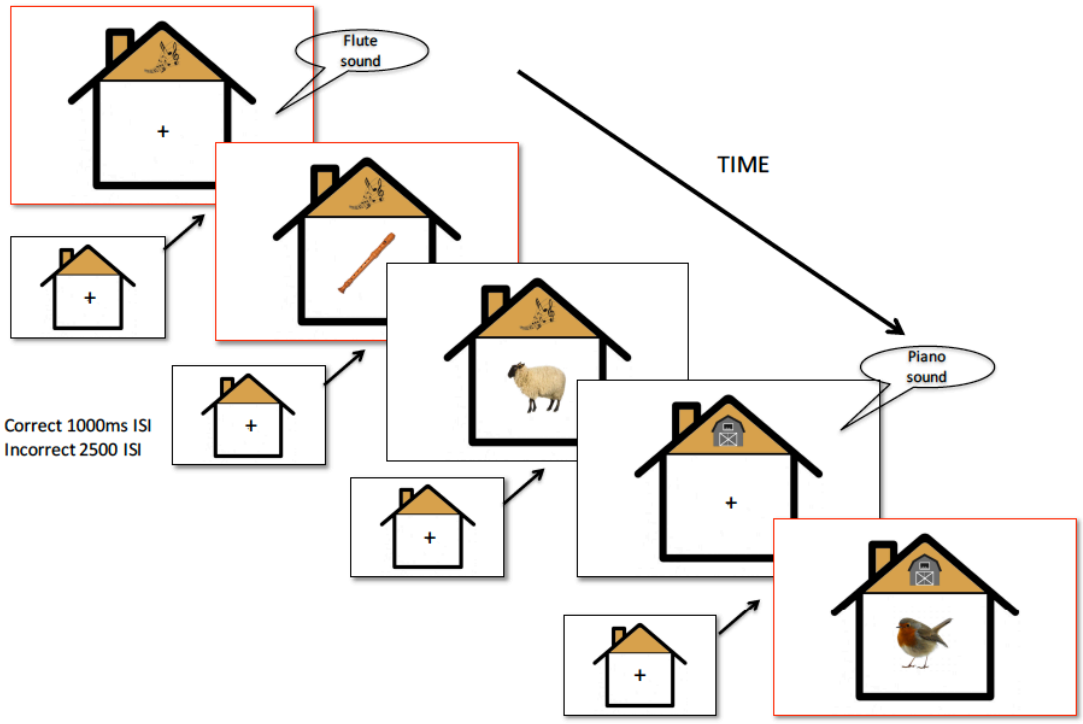

Figure 4.1. Schematic illustration of experimental design. All stimuli were unimodal (either just a sound or just a picture). The experiment involved switching between musical instrument task cued by the musical symbol on the roof, and an animal detection task cued by the barn sign on the roof. ISI (inter-stimulus-interval) was 1000ms for a correct response, and 2500ms for an incorrect response.

There were 10 different colourful pictures (approx. 3.8cm x 3.8cm) and 10 different sounds (approx. 60dB; 42,000 Hz) in each target category (animal vs. musical instrument). The stimulus timed out after 3000ms if no response was made. The target was presented centrally on the screen inside a cartoon drawing of a house (11.4cm x 11.4cm). The task cue was presented above the target as a banner of the house. The inter-stimulus-interval (ISI) was 1000ms for a correct response, or 2500ms for an incorrect response. A continuous background neutral water sound was played at approximately 45dB throughout

the experiment, in order to match with the continuous presentation of visual information. The participants received no feedback for the responses.

The experiment involved 120 trials separated into 5 blocks (24 trials per block). Tasks changed unpredictably in each block, with a 60% chance of a correct target appearances (i.e. the number of correct target appeared on 72 trials). Stimulus modality was chosen randomly with an equal probability. The experimental manipulation resulted in a number of cells for four specific trial types: modality-repetition task-repetition (MRTR, M=16.5, SD=3.7), modality-repetition task-switch (MRTS, Mean=17, SD=3.9), modality-shift task-repetition (MSTR, Mean=19, SD=2.8), and modality-shift task-switch (MSTS, Mean=19.5, SD=3.1).

The experiment was administered on a MacBook Pro Retina with 1440x900 pixels, run on 2.3 GHz Intel Core i7. Child-friendly closed-back headphones were used for presenting the auditory stimuli. The participants made a response by pressing the central spacebar highlighted with a green sticker. Both accuracy and response times were measured.

4.2.3 Procedure

Children were seated approximately 45cm in front of the laptop. The experiment was divided into four parts—a category session, a demonstration session, a practice session and the testing session. The category, the demonstration, and the practice sessions were conducted with Microsoft PowerPoint. The dependent measures of RT and accuracy were recorded only in the testing session, which was implemented using Matlab R2014b and Psychophysic Toolbox extensions (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997).

4.2.3.1 Categorization, Demonstration and Practice Sessions

The categorization session was designed to make sure that the children understood the categories of the stimuli. There was an auditory categorization task and a visual categorization task, each consisting of 10 trials of pseudorandom presentation of music and animal sounds/pictures. The participants were asked to verbalise whether the sound/picture they were presented with was an animal or a musical instrument. The experimenter made sure that the participant named the category (animal vs. music) and not the actual label of the animal or the musical instrument. The participants who made more than 2 errors in either task were excluded from participating in the test trials used for analyses but were congratulated and given certificates for participating like all other children.

The demonstration and the practice session each consisted of 4 trials of each task (total 8 trials). The first two trials of each task in the demonstration were target trials (one visual target and one auditory target) and the last two trials were non-target trials (one visual non-target and one auditory non-target).

Before the demonstration trials began, children were shown a slide with two houses and were given the instruction as following, ‘we have two different houses here. This house over here is a music hall (pointing to the music hall). I know it is a music hall because it has this symbol on the roof (pointing to the task cue). Can you see the symbol on the roof?’ The experimenter waited for the child to answer. ‘In the music hall, different music is being played. If you find yourself in the music hall, I want you to look for music for me. You might see it in the house, or you might hear it in your ears, but whenever you find music in the music hall, I would like you to tell the computer by pressing the green button (indicating the space bar highlighted with a green sticker).’ A similar instruction

was given for the barn house where the participants were instructed to look for animals instead.

The first 4 demonstration trials were examples of the music hall game. A target trial was shown and the experimenter would say ‘Oh here is a music hall (pointing to the cue). We are looking for music.’ The experimenter would pause for approximately 1 to 3 seconds depending on whether it was a visual stimulus or an auditory stimulus. ‘Now tell me, did you see/hear a musical instrument?’ The experimenter would go over the trial again if the participant gave an incorrect answer. After getting the correct affirmative answer, the experimenter told the participant to press the spacebar to let the stimulus into the house if it is a music instrument, or to wait and do nothing it is an animal (participants were also told that if the animals got into the music hall, they would make a mess inside the music hall; and the equivalent story for the ‘barn house’ game was that if music was being played in the barn house, it would wake up the sleeping animals.).

In the practice session, the experimenter told the participant ‘Now I want you to have a little practice before we start the real game.’ When the first trial came up, the experimenter hinted, ‘Oh it is a music hall/ barn house. If you find a musical instrument/ an animal, press the button’. The hints were given on every trial until the experimenter was confident that the participant understood the rule. There were 8 trials in the practice session, and 4 TS (task-switch) trials and 4 MS (modality-shift) trials presented in a predetermined but unpredictable sequence to the participants.

4.2.3.2 Testing Session

During the testing session, the participants were given trials that were randomised according to task and modality. The experimenter told the participants that they should respond as quickly and as accurately as possible. For the first four trials the experimenter gave verbal reminders to the participants. The verbal reminder was, 'Here is a music hall/ barn house. If you see/hear music/animal, press the button.' A total of 120 trials were equally separated into five blocks by a motivational screen offering a rest-break if needed. Children saw the simultaneous presentation of a task cue and the stimulus for a maximum of 4000ms or until a response was made, followed by a variable inter-stimulus-interval (ISI), dependent on the responses—for a correct response, the interval was 1000ms; for an incorrect response, the interval was 2500ms to allow a recovery period (Fig 4.1). A fixation cross was shown during the ISI. The response window was kept between 300ms and 3800ms after the stimulus onset. The lower bound was designed to exclude anticipatory response and the upper cap was designed to allow for a 200ms gap to process motor feedback (i.e. disappearance of the stimulus and the refreshed screen).

4.3 Results

Both reaction time and accuracy were measured in this study. The between-subject factor was Age and the within-subject factors were Task Transition (Task Switch vs. Repetition), Modality Transition (Modality Shift vs. Repetition), and Response Transition (Response Single vs. Response Repetition). The first trial in each block was excluded from the final data since these trials do not correspond well to a specific trial type (i.e. it is not a switch/repetition of task/modality). Only the correct positive trials were included

in the RT analyses. The current study made no assumption about the distribution of the RT samples for each participant. Instead, the bootstrapped mean RTs of each participant were obtained by resampling the RT data for 5000 times thereby ensuring that the data was normally distributed (Bollen & Stinet, 1990). The case for adopting a bootstrap method is particularly valid with the limited RT samples as in the current experiment. The alpha level was set at .05 across all planned comparisons. Unless reported otherwise, all *main effects* of Age in the analyses reported below were significant at $p<.05$ level.

4.3.1 Overall accuracy and RT

Figure 4.2 shows the reaction times (RT) and the accuracy of each age group. All ages achieved high accuracy—4-year-olds (88%±1.6)[1], 6-year-olds (95.9%±0.5), and adults (97.9%±0.7). Younger participants were slower than older participants—4-year-olds (2005ms±65), 6-year-olds (1595ms±58), adults (1020ms±39).

Preliminary analyses using univariate ANOVA were carried out to investigate the between-subject effects of Age on RT and Accuracy. There was a significant effect of Age on both RT ($F(2,69)=84.42$, $p<.001$, $\eta^2=.710$) and Accuracy ($F(2,69)=25.25$, $p<.001$, $\eta^2=.423$). Post-hoc t-tests (Bonferroni corrected to alpha=.017) on RTs showed significant differences among all pairwise comparisons (4-year-old vs. 6-year-old, $t(49)=4.692$, $p<.001$); 6-year-old vs. adults, $t(48)=8.093$, $p<.001$; 4-year-old vs. adult, $t(47)=12.814$, $p<.001$). Only 4-year-olds were significantly less accurate than the older participants (4-year-old vs. 6-year-old, $t(49)=4.633$, $p<.001$; 4-year-old vs. adult, $t(47)=5.492$,

[1] All cited errors are standard errors of means.

p<.001). There was no significant difference in accuracy between 6-year-olds and adults (6-year-old vs. adults, $t(48)=2.343$, $p=.025$, n.s.) .

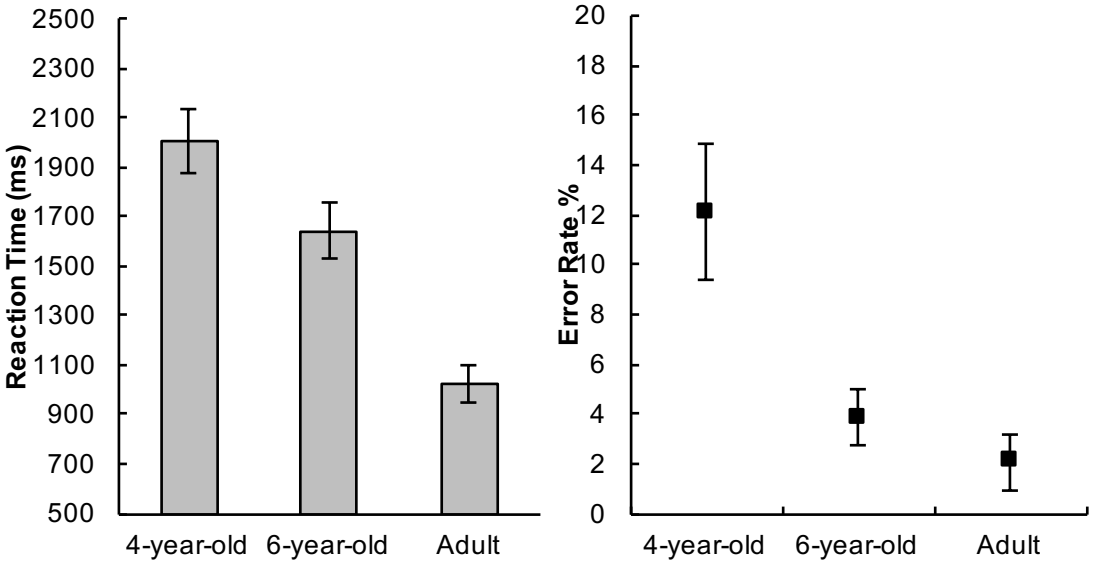

Figure 4.2. Mean RTs and error rates in each age group. Error bars represent 95% confidence intervals of means.

4.3.2 Target modality

4.3.2.1 Reaction Time

We first looked at whether there were any age differences in how visual and auditory stimuli were processed. Mean values showed that the participants were quicker when responding to visual targets (1520ms±58) than to auditory targets (1580ms±57) (see Fig 4.3). Two-way mixed ANOVA was carried out with Target Modality (visual vs. auditory) as the within-subject factor and Age as a between subject factor. The main effect of Target Modality was significant, ($F(1,72)=6.52$, $p=.013$, $\eta^2=.083$) demonstrating that responses to visual targets were quicker than to auditory targets. There was no Target Modality by Age interaction in RT ($p>.700$).

4.3.2.2 Accuracy

Figure 4.3 shows that the accuracy was higher for visual targets (95.75%±0.88) than auditory targets (92.55%±1.3). The main effect of Target Modality was supported in the two-way ANOVA with Target Modality as the within-subject factor and Age as the between-subject factor ($F(1,72)=13.15$, $p<.001$, $\eta^2=.154$). The main effect of Target Modality was moderated by an interaction between Target Modality and Age ($F(2,72)=4.32$, $p=.017$, $\eta^2=.107$). The interaction was followed up with separated analyses within each age group, which showed that only 4-year-olds were significantly less accurate to auditory targets than visual targets ($F(1, 24)=9.30$, $p=.006$, $\eta^2=.279$), all other groups showed no difference in accuracy between targets of either modality ($ps>.100$).

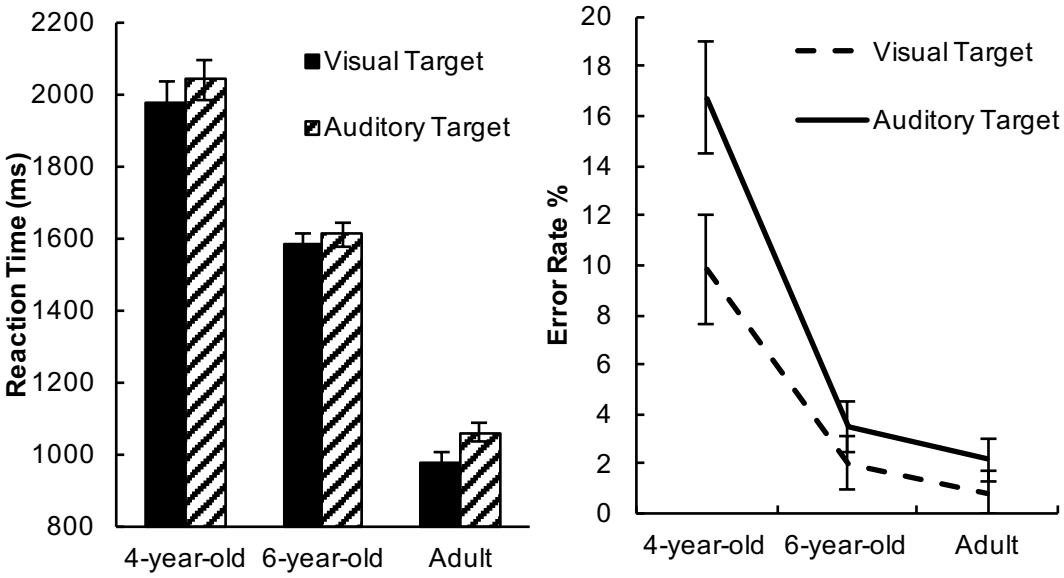

Figure 4.3. Reaction Time and Error Rate to Visual and Auditory Targets. Error bars represent 95% within-subject confidence intervals of means (Cousineau, 2005).

4.3.3 Modality-shifting and task-switching

4.3.3.1 Reaction Time

Mean RTs were longer on TS (task-switch) trials (1584ms±58) than TR (task-repetition) trials (1519ms±56) (see Fig 4.4); and longer on MS (modality-

switch) trials (1570ms±57) than MR (modality-repetition) trials (1532ms±58) (see Fig 4.5).

The effects of modality-shifting and task-switching were analysed with a three-way mixed ANOVA with Age as the between-subject factor, Modality Transition and Task Transition as within-subject factors. The main effect of Task Transition was significant ($F(1,72)=25.111$, $p<.001$, $\eta^2=.259$), as well as the main effect of Modality Transition ($F(1,72)=4.541$, $p=.037$, $\eta^2=.059$). There was no interaction either between the effect of Task Transition and Age ($p>.400$); nor between the effect of Modality Transition and Age on RT ($p>.400$).

We hypothesised that shifting modality would benefit switching task, and expected to find an interaction between Modality Transition and Task Transition. Contrary to our prediction, there was no interaction between Task Transition and Modality Transition on RT ($F(1,72)=.96$, $p>.300$, $\eta^2=.013$), nor was there a three-way interaction between Task Transition, Modality Transition and Age ($p>.300$).

4.3.3.2 Accuracy

Mean accuracy was greater on TR trials (94.41%±0.80) than on TS trials (93.34%±0.84), and the effect of Task Transition on Accuracy was significant ($F(1,72)=4.345$, $p=.041$, $\eta^2=.057$, see Fig 4.4). In contrast, the effect of Modality Transition on Accuracy was not significant (p>.200, see Fig 4.5). There was no further interaction between Task Transition and Modality Transition ($F(1,72)=2.30$, $p>.100$, $\eta^2=.032$), nor a three-way interaction with Age ($p>.300$).

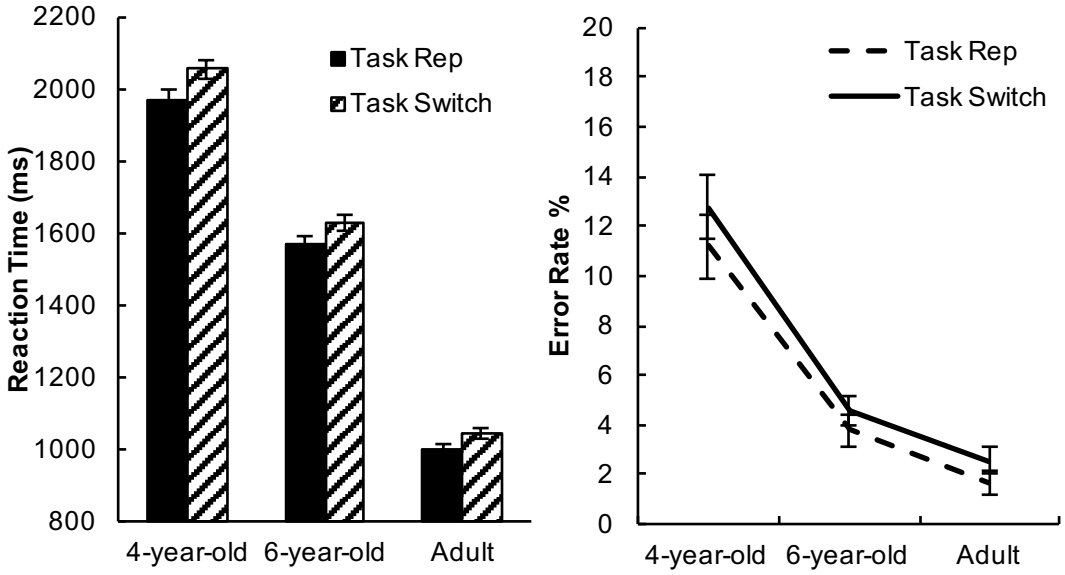

Figure 4.4. Reaction time and error rates on Task-Repetition vs. Task-Switch trials. Error bars represent 95% within-subject confidence intervals of means (Cousineau, 2005).

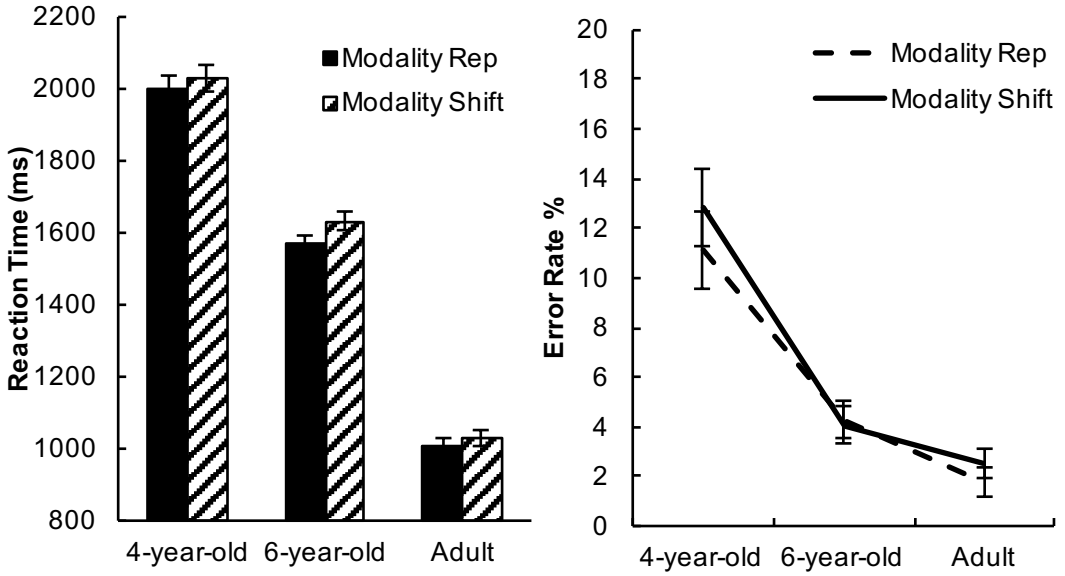

Figure 4.5. Reaction time and error rates on Modality-Repetition vs. Modality-Shift trials. Error bars represent 95% within-subject confidence intervals of means (Cousineau, 2005).

4.3.4 Cross-modal task-switching (CMTS) cost vs. combined cost

While the task-switching effect was similar in both the modality-shift trials and the modality-repetition trials, the effect of CMTS might manifest itself not in terms of a reduction of TS cost, but as a cost subadditive to the combined TS and MS effects. To understand this, we calculated the CMTS cost and the combined cost. The CMTS cost is the RT differences between MSTS trials and MRTR trials. The combined cost is the overall cost of TS cost (RT differences between MRTS trials and MRTR trials) and MS cost (RT differences between MSTR trials and MRTR trials). Mean RTs showed that the CMTS costs and the Combined costs were very similar (Fig 4.6).

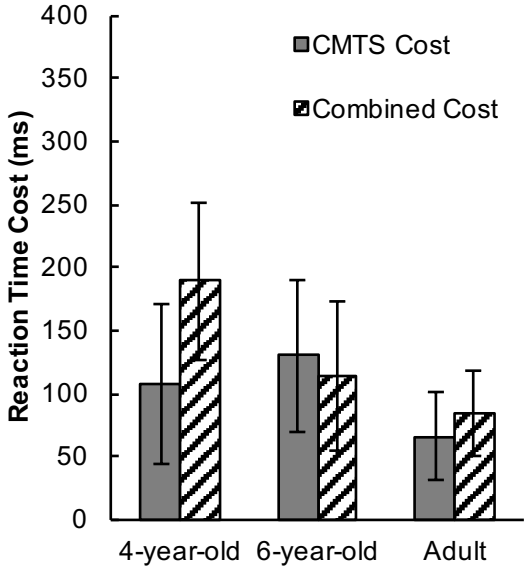

Figure 4.6. Cross-modal Task-Switching Cost and Combined Cost in reaction time in different age groups. Error bars represent standard error of means.

A two-way mixed ANOVA was carried out on Cost Type as the within-subject factor (CMTS cost vs. combined cost) and Age as the between subject factor. The result returned no significant main effect of Cost Type (p>.300), nor any interaction with Age (p>.300). The overall result failed to find any facilitative

effect of CMTS on task-switching, or as a subadditive cost to the combined TS and MS costs.

4.3.5 Response-repetition on task-switching and modality-shifting

Mean RTs indicated that the participants were quicker at responding when the trial was preceded by a response (Response Repetition, RR) than when it was not preceded by a response (Response Single, RS). Figure 4.7 shows the effect of Response Transition in different Trial Types (task-repetition, task-switch; modality-repetition, modality-shift).

The effect of Response Transition was analysed with the respect of Task Transition with a three-way mixed ANOVA (within-subject factors: Response Transition and Task Transition, 2 levels each; between-subject factor: Age). Only correct responses were analysed. The mixed model showed that there was a significant main effect of Response Transition ($F(1,72)=15.899$, $p<.001$, $\eta^2=.181$), which was superseded by a significant higher-order interaction between Response Transition and Task Transition ($F(2,72)=5.28$, $p<.024$, $\eta^2=.068$). There was no further interaction with Age ($p>.400$).

The interaction between Response Transition and Task Transitions were followed up by analysing the effect of Response Transition on TS trials and TR trials separately, with all ages collapsed together. The effect of Response Transition was only evident on the TR trials ($F(1,74)=19.83$, $p<.001$, $\eta^2=.211$), but not on TS trials ($F(1,74)=1.81$, $p=.182$). The interaction indicates that when the task repeated, responses were faster on the RR trials (1451ms±56) than on the RS trials (1545ms±57); in contrast, when the task switched, response times were similar on the RR trials (1564ms±60) and on the RS trials (1592ms±58).

The result is consistent with the past literature that response repetition is only facilitative when the task repeats, but not when the task switches.

Similarly, Response Transition was also investigated with the respect of Modality Transition (Response Transition and Modality Transition were entered as within-subject factors, and Age as a between-subject factor), on RTs of correct responses. While the main effect of Response Transition remained significant (p<.001), in contrast to the interaction between Task Transition and Response Transition, there was no two-way interaction between Response Transition and Modality Transition (p>.500). This demonstrates that responses were faster on the RR trials than on the RS trials irrespective to modality transition. There was no further interaction with Age (p>.200).

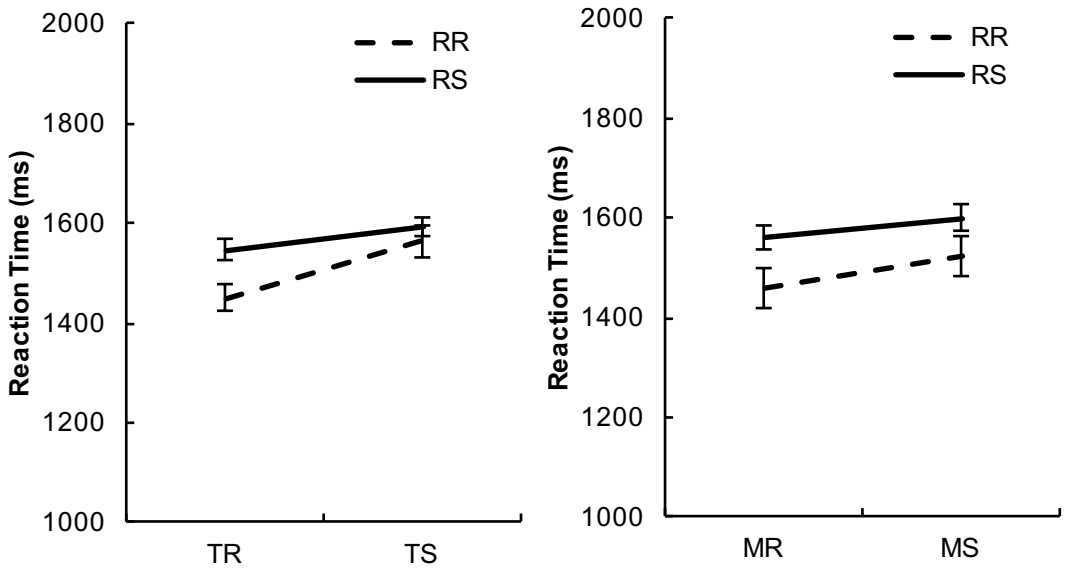

Figure 4.7. Response Repetition (RR) Effect under different attentional transition. Left panel shows RR effect and Task Transition; right panel shows RR effect and Modality Transition. RR: Response-Repetition; RS: Response-Single. Error bars represent 95% within-subject confidence intervals of means (Cousineau, 2005).

4.4 Discussion

Using a novel task-switching procedure that involved unpredictable task-switching and modality-shifting, the current study found reaction time costs associated with task-switching and modality-shifting. The patterns and the magnitude of either task-switching or modality-shifting costs were similar across all ages, as young children did not exhibit larger RT and accuracy costs than adults. The lack of a strong age effect on task-switching cost from preschool years is consistent with our previous unimodal TS and bimodal CMTS studies (Chapter 2 and 3), as well as other developmental studies (Dibbets & Jolles, 2006; Huizinga et al., 2006; Peng, Kirkham, & Mareschal, 2018; Wolff, Roessner, & Beste, 2016). However, past studies, including our previous studies, generally involved a long preparation window which may have obscured the age differences in the preparation component of task-switching. In the current study, advanced preparation was not encouraged as the task cue and the stimulus onset were synchronous. Even under this challenging condition, we did not observe any age interaction with either task-switching or modality-shifting costs. As the current study involved participants with a large age range, the lack of age interaction with any mode of attentional shift is particularly striking. The overall result illustrated that children as young as four were adept at switching attention between modalities and between tasks.

Although we found no differential age effect on the size of the attentional shift cost (for both task transition and modality transition), children were still slower and less accurate than adults. It is not clear what contributes to the overall lower performance in young children. One possibility is that different cognitive processes involved in task switching may have different timescales for maturation. For example, Weeda and colleagues (Weeda, Van der Molen,

Barceló, & Huizinga, 2014) have suggested that processes that contribute to proactive interference from the competing task set may mature relatively early, whereas the preparation and top-down component may have a longer maturation timescale. It remains possible that although young children in our experiment did not exhibit greater within-subject performance costs by transition types, they were nonetheless more likely to be unprepared than adults for the upcoming task, resulting in lower overall accuracy and longer RT than observed in adults.

Our main interest was to investigate whether there are developmental differences in the facilitative or subadditive effects of cross-modal task-switching, through which we can have a glimpse into the organization of information processes in different age groups. Specifically, we hypothesised that younger children would experience a greater attentional bottleneck and show additive costs to shift attention between modality and task. This hypothesis was based on past findings reporting that younger children showed greater engagement with the frontal network when shifting attention across modalities, consequently suggesting a more effortful switch of attention through top-down mechanism (Johannsen & Röder, 2014). In contrast, adults would be more likely to have a more mature segregated system to deal with information interference, and exhibit a cross-modal task-switching benefit as compared to the combined cost. To our surprise, we found no age interaction in the pattern of cross-modal task-switching cost. Furthermore, there was no evidence of a facilitative or a subadditive effect of cross-modal task-switching, in which modality-shift benefits task-switching, in any of the age groups. To our knowledge, this is the first study that reported an absence of benefit of simultaneous task and modality change.

Our result suggests that a common attentional resource between task-switching and modality-shifting is engaged during the current experimental paradigm. The result lends partial support to the previous studies that modality-shifting and task-switching are at least somewhat interdependent (Hunt & Kingstone, 2004; Sandhu & Dyson, 2012). Although our result did not report a subadditive effect, it remains possible that parts of the processing pathways can be independent. One explanation for the disparate finding between the current and the past findings may be that the level of cost/benefit from a cross-modal event is dependent on the selection processes among the intermixed components between task sets. If the benefit of modality-shift on task-switch trials stems from the reduced interference among the inter-trial information pathways, it may not be surprising that the degree of benefit is also dependent on the degree of pathway overlaps. Tasks with a greater degree of intermixed components between task sets may afford more opportunities for the cross-modal facilitative/ subadditive effect to emerge. The current study is relatively low in the selection demand from the intermixed representations, in either modality, task or response, as compared to other choice-based cross-modal task-switching studies with bimodal inputs, overlapping task attributes and responses. As a result, cross-modal facilitation may have little to act on to alleviate the already-small interference.

In task-switching studies, task transition has a cost-benefit relation with response repetition; response repetition benefits performance on task-repetition trials, but impedes performance on task-switch trials (Meiran, 2000; Rogers & Monsell, 1995; Wylie, Javitt, & Foxe, 2004). The phenomenon can be explained by primed S-R event on the previous trial. When both response and task repeats, there is a priming facilitation from the previous S-R event. In contrast,

when the task switches, the same response activates the irrelevant S-R event, creating a competition between the current and the previous S-R events (Waszak et al., 2003). A similar pattern of response repetition effect was also found in the current study, as the benefit of response repetition was only evident on task-repetition trials, but not on task-switch trials.

In contrast, modality transition did not show the same constraint on response repetition as task transition. Response repetition was facilitative to reaction time regardless of whether the target modality was the same or different from the target modality on the previous trial. This indicates that modality is not an important constituent in the S-R event, or perhaps in the task representation itself, in the present study. Although a previous study on modality shift effects suggests that modality is a constituent of the S-R event (Cohen & Rist, 1992), without a well-defined task that encompasses both auditory and visual modalities, it is not clear if the effect comes from modality-specific or task-specific components. Our result shows that, when the task goals are supramodal, modality information does not necessary form part of the episodic profile. This also implies that the processing cost associated with modality-shifting is likely to differ from the costs associated with task-switching, as modality-shifting is unlikely to change the whole S-R event as task-switching does. Importantly, both young children and adults showed similar interactions among response transition, modality transition and task transition. This indicates that both children and adults processed task, modality and response information in a comparable manner, formed similar mental representation of the task context, and are likely to engage the same cognitive operations in cross-modal task-switching tasks.

In the next few chapters I will present a series of connectionist computational models of performance in the bimodal cross-modal study (Chapter 3), since the study measured multiple task-associated and modality-associated effects measured (see Chapter 1, section 1.8.2 for the overviews of computational models in each chapter). These models will explore the effect of different information processes in each network age (Young, Middle and Old networks), and attempt to understand how different performance measures (RT, accuracy, mixing effect, switch effect, priming cost, priming facilitation, and modality shift effects) relate to the model parameters. The models will also address how individual differences may emerge at each network age.

Chapter 5. Computational models of task-switching (Model 1)

5.1 Gilbert and Shallice's Interactive Activation (IA) Network

Interactive Activation (IA[1]*)* is a cognitive computational model with parallel processing units. The model was first proposed by McClelland and Rumelhart (1981) to investigate the effect of feature detection in word processing. It was later adopted by Gilbert and Shallice (2002) to investigate task-switching effects in Stroop tasks. Specifically, they were interested in the RT cost associated with switching to an alternative task, and the asymmetry of switch costs from one task to the other. The model has been successful in proposing the plausible mechanisms for the cognitive component of switch cost, and the carry-over interference of switch costs through priming interference. Thus, it has already proven to be valuable in elucidating the multiple components of task- and switch- related processes in adults.

Gilbert and Shallice's IA model specifies different levels of cognitive processing—a perceptual level, a task attribute level, a top-down control level, and a response level. Each level has a specific number of units, assigned with a specific attribute. With a specified architecture, the units are interconnected within the same level and/or between different levels. The connections between the units have fixed weights. Moreover, each unit in the model behaves like a simple accumulator of the incoming inputs—the activations are passed around

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[1] Glossary of terminology throughout this thesis can be found in the Appendix A

directly within the network without passing through non-linear unit activation functions that govern the 'on/off' status of the unit.

In Gilbert and Shallice's IA model, the network was divided into two main pathways, each associated with a specific task (colour vs. word task pathways, see Fig. 5.1). There were several layers of representations—(i) a percept stimulus input layer with units representing stimulus attributes (in this case either a word or a colour), (ii) a top-down control input layer with a single input source representing top-down control, (iii) a task attribute layer (or task-demand in their model) with two units representing either a colour task or a word task, and (iv) a response layer with units associated with either the colour task pathway or the word task pathway. Some of the units (top-down unit and percept stimulus units) were simply input units. These units had their activations clamped to a specific input value when required. Other units such as task attribute units and response units were processing units with continuously updated activation throughout the trial.

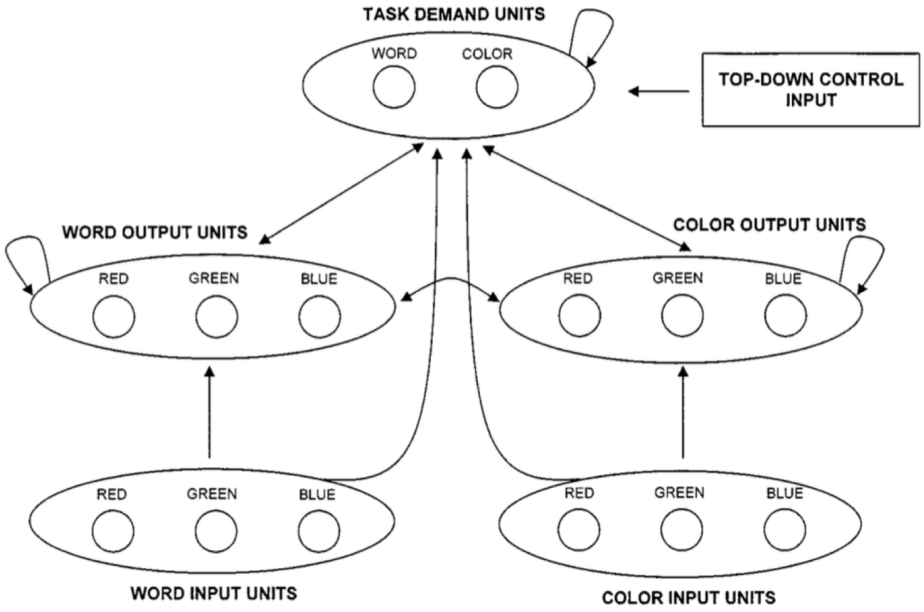

Figure 5.1. Interactive activation in Gilbert and Shallice's task-switching model (2002).

Gilbert and Shallice's task-switching model has several advantages for the investigation of cognitive processes. Firstly, the model architecture with theory-led cognitive components allows easy visualization of the interactions among different processing levels. Being able to visualize the model also means that the principle assumptions about the architecture can be based on behavioural observations. For example, Gilbert and Shallice built temporary priming connections in the model to account for priming costs on switch trials. Secondly, the model assumes simple functions of the processing units, with a minimal transformation of the inputs, thereby limiting the assumptions of different processing levels. Thirdly, the model can be easily adapted to other types of task-switching experiments, and is sensitive to the contextual factors that may influence performance. By differentiating the associative connections between tasks, stimuli and responses, it is possible to build a task environment

corresponding to a specific behavioural experiment, rather than a generalized form of cognitive operation associated with switching between tasks.

Adopting the basic principles of the Gilbert and Shallice's IA model, I will describe a series of task-switching models designed to capture the results of the bimodal CMTS study (Chapter 3). The different architectures of my models will correspond to specific task contexts in bimodal CMTS. In the next section, I will outline the architectural details of Model 1. The basic architecture details of Model 1, which is the closest to Gilbert and Shallice's task-switching model, has the fewest assumptions on the information processes and the interactions within. The objective of Model 1 is to understand the basic dynamics within a relatively constrained architecture, and their relations to the response outputs on different trial types (pure, repetition and switch trials). Unless otherwise specified, the basic architecture and parameter setting in Model 1 will hold for all subsequent models described in the later chapters.

5.2 Network Architecture

5.2.1 Overview of Model 1

In Model 1, pure and mixed tasks were modelled with different network structures, resulting in mixed network (left network in Fig. 5.2) and pure network (right network in Fig. 5.2) architectures[1]. As in Gilbert and Shallice's Model, there were distinct layers of processing units in either the pure or mixed networks—a *Percept Stimulus (PS)* layer, a *Response Output (RO)* layer, a *Task Attribute layer (TA)* and a *Top-down signal (Top)* layer. Model 1 was

[1] All parameters setting used in the simulations in Chapter 5 are listed in Table 5.1 at the end of chapter.

organized with feedforward connections that feed inputs from both the PS and the TA units into the RO units. There were also lateral interactions through inhibitory connections among the units in the same processing layer. The function of the lateral interaction is to implement a selection process within the same processing layer (i.e. favouring one unit over the rest). Unit activations change by gathering evidence (i.e. incoming input) through the connected units. In addition to these fixed feedforward connections, there were temporary priming connections that simulated the inter-trial priming effect (dashed lines in Fig. 5.2). These priming connections were used to model carry-over effect in Gilbert and Shallice's model. The network runs through several updating cycles to gather evidence from the associated units. A response is deemed to have been made when the activation value of a response unit exceeds a set threshold.

Since a task-switching study focuses on participants' existing ability to switch between tasks, learning was not thought to be an important factor contributing to the overall performance. Therefore, all networks were constructed with the assumption that the participants in our studies understood the task instruction, and could form an appropriate internal representation of the overall task set. To reflect this non-learning nature of performance, all network was hand-wired. There was no stochasticity in the network other than adding a small amount of noise drawn from a normal distribution to the activation values on each processing cycle. The result is that the responses were by and large deterministic (i.e. pre-determined). Thus, in Model 1, the networks should achieve near ceiling performance; any error occurring would be the result of noise accumulation during the response settling process, rather than the direct

consequence of incorrect weight setting. All parameters are listed in Table 5.1 at the end of Chapter 5.

In the next few sections, I will describe the processing units, the connectivity within the network, as well as the governing functions within the network. Finally, I will detail the temporal operations of the networks.

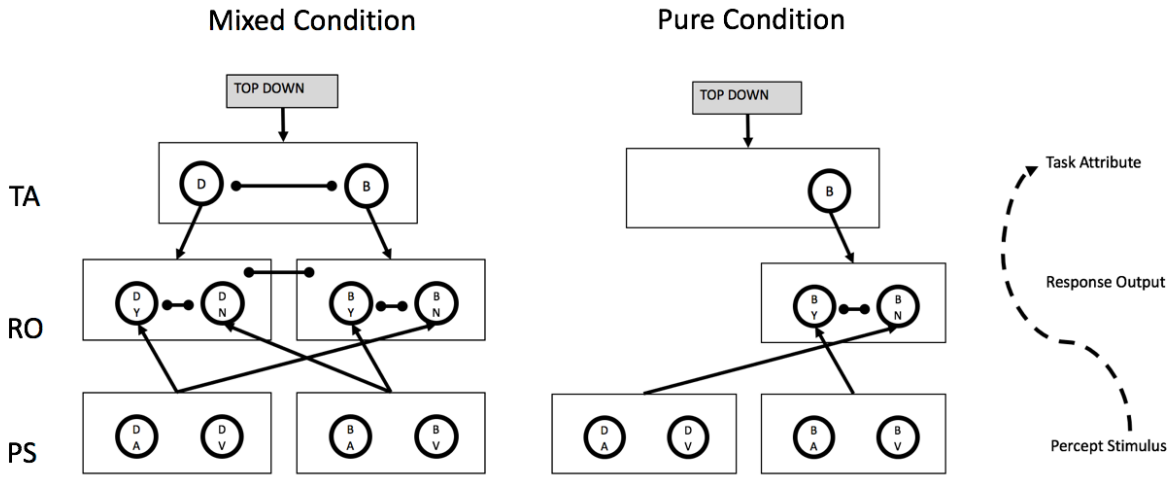

Figure 5.2. Model 1 architecture—Left: mixed networks; Right: pure networks. The networks have 4 layers: Task Attribute (TA) layer, Response-Output (RO) layer, Percept-Stimulus (PS) layer, and Top-down input. The dashed line represents temporary priming connections between PS units and TA units form on n-1 trial. See Figs 5.3 to 5.5 for details of the network units and operations.

5.2.2 Input units and processing units

The units in the networks can be defined as either input units or processing units. The input units have fixed values and are not subject to updates. The input units in our networks are the Percept Stimulus units (PS) and the Top-down signal (Top). In comparison, processing units are activation-based units and are subject to constant updates from the feedforward inputs and lateral interactions with the units of the same processing level. The

processing units are the Task Attribute units (TA), and the Response Output units (RO). Each unit is detailed below.

The *Top-down signal* (Top) is conceptualised as a domain-general endogenous signal to the lower-level processes. The Top signal sends a fixed value of input to the task-relevant TA unit. A greater Top signal excites the TA unit more strongly. The Top signal is clamped at a fixed value (e.g. Top=6).

The *Task attribute units* (TA) denote different task goals. In the pure condition, there is only one TA unit, since there is no competing task in the pure condition. In the mixed condition there are two TA units—one TA representing the 'to detect Dog' task and one TA representing the 'to detect Bird' task. These are processing units, which means that they continuously update the unit activation through gathering evidence from the associated units across successive processing cycles. The activation of a TA unit is synonymous with multiple cognitive operations including, but perhaps not limited to, cue presentation, cue-encoding, and the identification of task-relevant attributes. The activation value of the TA units is bounded between [-1 1].

The *Response Output* (RO) level contains four units in the mixed condition—a 'Dog-Yes' (DY) unit signifying a positive response to the dog category, a 'Dog-No' (DN) signifying a nonresponse to the dog category, a 'Bird-Yes' (BY) unit signifying a positive response to the bird category, a 'Bird-No' (BN) signifying a nonresponse to the bird category. In the pure task, there are only two RO units signifying either a 'Yes' response or a 'No' response, since there is only one target category.

The *Percept Stimulus units* (PS) refer to perceptual inputs in different modalities (e.g. visual and auditory). In the behavioural experiment, all stimuli were bimodal and consisted of one auditory input and one visual input. There

are four different PS units—Dog-Visual (*DV)*, Dog-Auditory (*DA*), Bird-Visual (*BV*) and Bird-Auditory (*BA*). These units, if active, have value clamped at 1. The same units are present in both pure and mixed networks.

In the mixed task of the bimodal CMTS experiment, both bird and dog stimuli were part of the target sets, while the cat and sheep stimuli formed the neutral set. Since all stimuli were bimodal, the use of target sets and neutral sets allow the formation of different trial types—target+neutral (e.g. DV+neural auditory), target+nontarget (DV+BA), or neutral+neutral. The neutral stimuli are not modelled here as it is assumed that the neutral information was easily ignored at the outset because it was not associated with any response set. Although one could argue that a neutral stimulus is associated with a 'No' response, it is not clear which 'No' response out of the competing response sets it should be associated with. It seems far more likely that the neutral information was instead ignored and thus that very little selection was involved. As a consequence, the stimuli on the simulated trial in the mixed network is either *bi-selection* (choosing between PS inputs, e.g. DV or BA), or *uni-selection* (only one PS input is present, e.g. BA).

The same logic is not applied to the pure networks. In the pure networks, the PS units from the nontarget animal category are essentially neutral input (e.g. bird PS units are neutral in the pure networks for Dog task). However, the inclusion of the neutral inputs is necessary for two reasons: firstly, including nontarget stimuli is necessary for regulating the probability of target appearance, and secondly, it is necessary to expand the response decision space to both 'Yes' and 'No' for a good match to the behavioural context. Consequently, all trials in the pure network involve uni-selection stimuli (either target 'DV' or nontarget 'BV' present). Despite including the neutral PS units,

the neutral PS units do not produce competition during the settling process, since there is no competing response set.

5.2.3 Network connectivity

5.2.3.1 Fixed feedforward connections

As mentioned previously, all fixed connection weights are hand-wired. Both PS units and TA units have feedforward excitatory connections into the RO units. The network architecture can be classified into two main task-associated pathways—a pathway associated with the dog detection task, and a pathway associated with the bird detection task. Each PS unit is connected to both Dog and Bird response sets (Fig. 5.3). According to the experimental instructions, a stimulus input can be associated with two response categories—(a) a positive detection to Task A, or (b) a negative detection to Task B (e.g. a 'Dog' input can be interpreted as 'presence of a dog' and 'absence of a bird'). Therefore, each stimulus input is associated with two different response sets. The connections between PS and RO have asymmetric pathways by modalities. Specially, the connection weights from visual percept stimulus (PS_{VIS}) are stronger than the connection weights from the auditory percept stimulus (PS_{AUD}). This is due to the observation that all ages were quicker in responding to visual targets than auditory targets in the bimodal CMTS study. This asymmetry is applied to both pure and mixed networks.

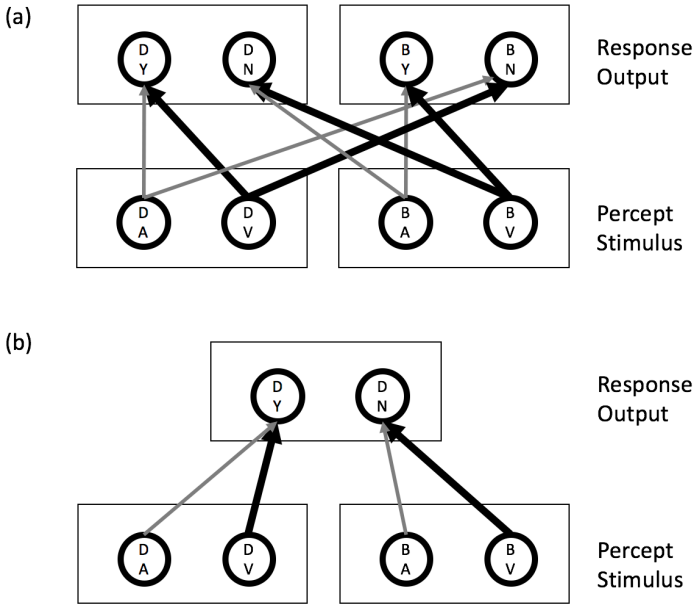

Figure 5.3. Feedforward connections between Percept Stimulus layer and Response Output layer in (a) mixed networks and (b) pure networks. Black connections represent stronger visual PS-RO pathways; grey connections represent weaker auditory PS-RO pathways.

Task attribute units have excitatory feedforward connections to the RO units of the corresponding categories. The connection strengths are the same between the two task-associated pathways (TA_{DOG} to $RO_{DY\&DN}$ vs. TA_{BIRD} to $RO_{BY\&BN}$ pathways); however, within each category pathway, the connection weights are different for the 'Yes' pathway and for the 'No' pathway. Task attribute units are strongly connected to the corresponding 'Yes' units, since the task instruction was to make a positive response for target detection, and weakly connected to the corresponding 'No' units (Fig. 5.4). Therefore, there is a bias towards making a positive response. This asymmetry is applicable to both pure and mixed networks.

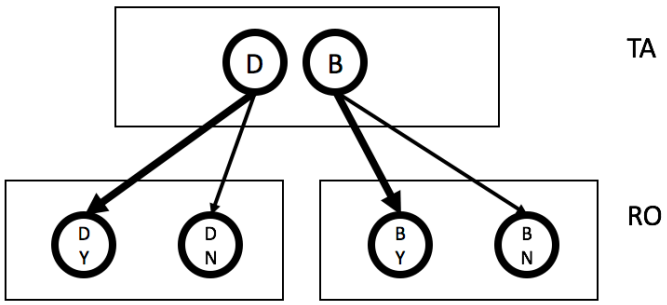

Figure 5.4. Feedforward connections from Task Attribute (TA) units to Response-Output (RO) units in mixed networks—stronger connections to the corresponding 'Yes' units and weaker connections to the corresponding 'No' units. The lateral inhibitory connections are symmetrical between the TA units. In pure networks, one of the task-associated pathway is omitted.

5.2.3.2 Lateral Inhibition connections

Units at the task attribute level and the response output level have reciprocal lateral inhibition connections to the other units in the same level. Mayr and Keele (2000) have argued that when two tasks are competing against each other, selection of the task-relevant attribute is likely to be accompanied by the inhibition of the competing task-irrelevant attributes (Mayr & Keele, 2000). At the response output level, it has been suggested that, on stop-signal tasks, there are likely to be inhibitory interactions between go and stop responses to facilitate response decision (Boucher, Palmeri, Logan, & Schall, 2007; Verbruggen & Logan, 2008). The inclusion of lateral inhibition also promotes settling among the RO units and increases the likelihood that only one response output reaches the response threshold.

The lateral inhibition connections between the TA units are symmetrical (Fig. 5.5, upper panel), since the tasks are presumed to have equal strengths.

The lateral inhibition connections are also symmetrical between the response sets (RO_{DOG} vs. RO_{BIRD}), but are asymmetrical within the response set (Yes/No) (Fig. 5.5, lower panel). Competing response sets (RO_{DOG} vs. RO_{BIRD}) strongly inhibit each other, thereby enabling the network to settle into one response set only. In comparison, the 'Yes' unit strongly inhibits the 'No' unit within the same response set (e.g. RO_{BY} strongly inhibits RO_{BN}). It is assumed that once the Yes unit is activated, it is relatively easy to inhibit the 'No' unit. In contrast, the 'No' unit only weakly inhibits the 'Yes' unit within the same response set. As a consequence, settling to a 'No' response requires a greater number of cycles. This asymmetric inhibition is also an optimal strategy for bi-selection trials. Bi-selection trials involve stimuli with two competing PS units (e.g. DA paired with BV). On these trials, even when an appropriate task is selected, the competition between the RO units within the response set is strong since the PS units send positive input to both Yes and No responses with the same response set. Selection is optimised if the processing is biased towards the 'Yes' response. The stronger lateral inhibition from Yes to No, coupled with the stronger TA unit to RO_{YES} pathway, means that the network requires weaker evidence from the perceptual stimulus to make a 'Yes' response than a 'No' response on bi-selection trials.

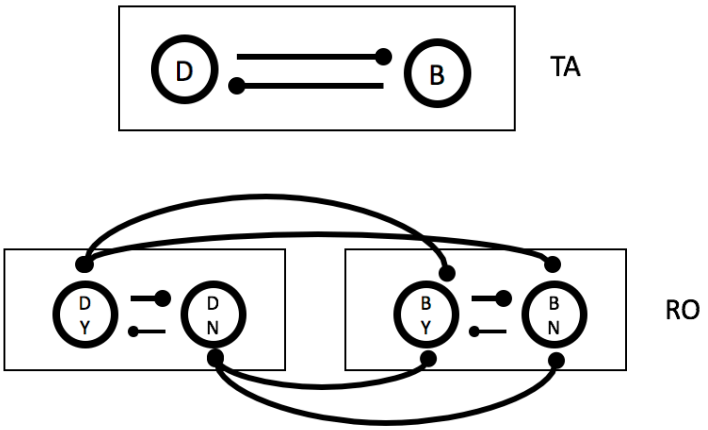

Figure 5.5. Lateral inhibitory connections in the mixed networks. Upper network shows the symmetrical lateral inhibitions between TA units. Lower network shows lateral inhibition between RO units—strong inhibitory connections between response sets; strong inhibitory connection from 'Yes' to 'No', and a weaker inhibitory connection from 'No' to 'Yes' within a response set. In the pure networks (not shown here), there is no lateral inhibition at TA level, and only the asymmetric lateral inhibition within the response set.

5.2.3.3 Priming connections between PS and TA (PS2TA)

Other than the fixed excitatory and inhibitory connections mentioned earlier, there are also temporary feedforward connections from the PS units to the TA units (Fig. 5.2, dashed line). These connections create the n-1 stimulus-task primes. These connections are formed through hebbian-like learning mechanism between the activated PS unit(s) and the TA units (both activated and inhibited units) at the end of each trial. These temporary connections are the only connections that undergo associative learning; however, unlike learning that results in fixed structural changes that affect all future behaviours, the learning here lasts for one trial only. The same priming connections were also present in Gilbert and Shallice's models, and were crucial to account for the

interference component of switch costs. If any identical percept stimulus unit is reactivated on a following trial, the percept stimulus unit(s) will send activation to the task attribute unit(s) relevant to the n-1 trial. It should be noted that both excited and inhibited TA units have temporary priming connections with the PS units, and therefore the primes can either have positive input or negative input to the TA units.

On a task-repetition trial, the priming effect is facilitative since it increases the activation of the relevant task attribute, and decreases activation of the competing TA unit. In contrast, on a task-switch trial, the priming effect would be interfering since the prime is likely to send positive input to the competing TA unit, and negative input to the task-relevant TA unit.

The priming connection weights are the product of the activation values between the PS and TA units at the end of the n-1 trial (Equation 1).

$$W_{ij} = Irate \times a_j \times a_i \qquad \text{(Equation 1)}$$

The a_j is the activation of the PS unit, and the a_i is the activation of the TA unit. Irate is the learning rate of the weight change, which determines the magnitude of the priming effect. These connections are rewired, rather than updated, after each trial. Therefore, the memory of the connection lasts for one trial only. Since our studies only looked at n-1 trial effect, no other assumptions are made about other potential higher-order trial sequence effects, although higher order effects might be present.

5.2.4 Temporal dynamics and unit update functions of the model

The network operates with a set of functions and operational parameters. In this section I will illustrate the temporal dynamics of a trial. The information

processes within the network are largely parallel; however, there are still distinct events to match with the experimental procedure.

As with the experiment, each trial starts with a long *preparation window*. During the preparation window, the Top unit sends input to the task-relevant TA unit, while all other units remain inactive (i.e. unit activation=0). Past studies have suggested that task-preparation is a two-stage process (Mayr & Kliegl, 2000; Monsell, Yeung, & Azuma, 2000)—during the preparation window, the participants only prepare for the abstract goal-setting (e.g. 'to detect Dogs'), but the specific rules governing the response set are only activated after the stimulus onset. Thus, during the preparation window, only the task-relevant TA unit, which corresponds to the task goal, is updated through Top input. The competing TA unit is updated through lateral inhibition. RO units and PS units are inactive (activation=0) during this period. The longer the preparation window, the greater the activation of the task-relevant TA unit is, and the greater the inhibition of the task-unassociated TA unit. TA units are updated with the unit update function detailed in the subsection 5.2.4.1.

After the preparation window, one (i.e. in case of uni-selection) or two (i.e. in case of bi-selection) PS units are activated and the value of the PS unit is clamped at 1 throughout the trial. Once the PS units are activated, all unit updates are carried out in parallel. The RO units are updated at each update cycle until the response threshold is reached in one of the RO units. The number of update cycles is taken as a measure of reaction time.

Before the next trial begins, TA activations are assumed to decay. The decay is modelled with a squashing parameter (*Squash*), that reduces the magnitude of the TA activation to a certain percentage of the original level. In the current model, there is no formal commitment to what the squashing

parameter represents in cognition. For example, it could represent cognitive effort associated with not perseverating in a specific task representation, or natural memory decay, or both. The squashing function applies to both excited and inhibited TA units. In comparison, all units other than the TA units are set to an inactive state of '0'.

5.2.4.1 Unit update function

The activations of all processing units (TA and RO) are capped between a minimum of '-1' and a maximum of '+1'. The net inputs (Net_i) to the unit 'i' is simply all the products between the connection weight (W_{ij}) and the input unit 'j' activation value and with a pre-defined *bias* as a threshold (i.e. the amount of positive input required to positively update the unit, i.e. -3 in the models) (Equation 2).

$$Net_i = \sum_j^n W_{ij} \times \text{unit 'j' activation} + bias \qquad \text{(Equation 2)}$$

The change in activation ($\Delta activation$) of the unit 'i' follows equation (3) and (4) below. The '*act*' in the equation refers to the current activation value of the unit 'i'. The *step* is the rate of the activation update, which is a pre-defined positive value (i.e. 0.0015 in our models). The unit update function has the notable characteristic that, given a specific *net* input (and a pre-defined *step*), the $\Delta activation$ is dependent on the difference between the current activation and the min/max values. If the difference is large, then the $\Delta activation$ is larger than when the difference is small. In addition to the activation updates caused by the inputs, noise '*u'* bounded between [-1, 1] is added to the activation of unit 'i' at each update cycle. The noise is drawn from normal distribution with a fixed

standard deviation (i.e. 0.006) around a mean of zero. The standard deviation of the distribution determines how noisy the system is.

$$If\ the\ Net_i\ is\ positive: \Delta activation = step \times Net_i \times (max - act_i) + u_i$$

(Equation 3)

$$If\ the\ Net_i\ is\ negative: \Delta activation = step \times Net_i \times (act_i - min) + u_i$$

(Equation 4)

5.3 Comparison with Gilbert and Shallice's model

Gilbert and Shallice's model had asymmetric connections between the two pathways associated with the competing tasks—stronger connections between the task attribute unit and the corresponding response units for the dominant task (i.e. word task), and weaker connections between the task attribute unit and the corresponding response units for the nondominant task (i.e. colour task). In our behavioural experiment, the participants switched between two animal detection tasks. It was assumed that the tasks had a similar level of difficulty, so an asymmetry between task pathways would not be appropriate in our case. However, our model did include other forms of asymmetric pathways, such as stronger pathway between TA and RO_{YES} than RO_{NO}, and stronger pathways from visual stimulus than auditory stimulus.

The models in the current thesis and Gilbert and Shallice's model differed in more ways than just the asymmetric pathways. In their model, in addition to the feedforward excitatory connections from the task attribute units to the corresponding (i.e. of the same task) response units, there were also inhibition connections from the task attribute units to the *competing* response output units. These inhibitory connections were selective in nature, so could be

thought of as functionally similar to an inhibitory control mechanism. In addition to the feedforward excitatory and inhibitory connections, there were also excitatory feedback connections from the response output units to the corresponding task attribute units. Gilbert and Shallice argued that this feedback mechanism simulated the effect of 'attentional capture' – i.e. of naturally drawing attention towards the representations associated to the stimulus itself. However, preliminary tests with our simulated models suggested that neither the inhibition feedforward connections nor the excitatory feedback connections were imperative for the overall performances. Additionally, these connections have much weaker theoretical justifications in the task-switching literature, at least in the case of 'attentional capture'. Although inhibitory control may be a candidate mechanism in successful task switches, as we have seen in Chapter 1, many inhibition phenomena could be explained by processes that are not associated with inhibitory control, such as selection processes. For these reasons, our models only included excitatory feedforward connections from task attribute layer to response output layer.

5.4 Simulation Schedule

All parameters setting used in these simulations are listed in Table 5.1 at the end of Chapter 5.

5.4.1 Simulation objectives

The aims of the simulation are (1) to examine whether mixing costs (pure task vs. mixed task) and switch costs (repeating task vs. switching task) can be successfully captured by Model 1, and (2) to understand what parameters are critical for inducing these between-condition differences. It is important to note that Model 1 was not intended to explore modality-associated effects. Although

the model includes asymmetric modality pathways in order to reflect the patterns observed in the behavioural data better, the main focus of this computational model was purely on task-associated performances. As we have seen in unimodal CMTS reported in Chapter 4, supramodal task goals in cross-modal context are largely amodal, and therefore task-associated effects and modality-associated effects should be investigated independently.

It is also worth pointing out that although pure networks have outwardly similar looking network architectures to those of the mixed networks, they differ in several important ways. In the pure networks, the response space extends to neutral elements, which are not present in the mixed networks. That said, the inclusion of a 'No' response in the pure network is purely practical (so that the probability of target appearances can be regulated and that it will be possible for errors to occur). There is no competition between task sets in the pure networks so the responses are by and large made through stimulus-response associations. In comparison, mixed networks do have competition between different task elements implemented by separating TA and RO into two pathways each. The PS units are associated with both tasks thereby creating a complex interplay between bottom-up and top-down influences in the mixed condition. Thus, Model 1 explores whether the differences between pure task performance and mixed task performance is due to the competition (or lack thereof) between task pathways.

With regards to switch effects, it was noted above that RT switch costs in the Gilbert and Shallice's simulations is due to both n-1 residual TA activations and priming effects. Errors were also more likely on switch trials than on task repetition trials in their model. However, the error rates in their model were very low (<5%) so a floor effect may exist in their model. In our behavioural

experiment, 4-year-olds' mean accuracy on all trial types was less than 90%. Consequently, it is not clear if the simple pure and mixed networks will be able to replicate the developmental differences in both RT and accuracy observed in different age groups.

The simulations were therefore carried out in two phases—(i) an initial phase of parameter searching using Model 1A, and (ii) a phase exploring developmental differences using Model 1B. In Model 1A, I examined how performance could be affected by different free parameters in the default (Old) networks. The free parameters in the first phase were: the preparation interval, the Top signal, and the priming rate. In the second phase, using Model 1B, I introduced different network ages by varying the weights of the fixed feedfoward connections, and tested the aforementioned free parameters in the resulting networks of different simulated ages.

5.5 Model 1A: Searching for the Parameter Space

All reported simulations in Model 1A were run with 25 networks with default fixed connection weights (see Table 5.1, at the end of the chapter). The number of network "subjects" matches with the number of participants in the behavioural studies. There was one block of 48 trials for the pure networks and 3 blocks of 48 trials (total 144 trials) for the mixed networks. All stimuli were selected randomly with a 60% probability of target appearances, consistent with the behavioural experiments. In the pure networks, all stimuli were uni-selection stimuli (i.e. only one PS unit was activated). In the mixed networks, the stimuli could be either uni-selection stimuli or bi-selection stimuli (i.e. one visual and one auditory PS units are activated).

In mixed networks, the task switched on every other trial, which is different from the behavioural study where task switched every 4 trials. In Model 1A, the task-relevant TA unit was already highly activated on the first repetition trial, and the TA activation values did not change much with an additional repetition trial. Although the frequency of task-switches can potentially be a mediating factor for task performance, this did not appear to be the case in our experiments. Children exhibited comparable performances in bimodal CMTS (task switched every four trials, Chapter 3) and unimodal CMTS study (task switched randomly, Chapter 4).

The first trials of each block were excluded from the analyses to avoid the first trial effect (i.e. resulting in long RT or error due to very small TA activation). As in the behavioural experiment, RT analyses were restricted to correct *Yes* responses only. In the behavioural experiment, responses were binary valued (either a button-press or not), and no differentiation of response sets was possible. In comparison, in Model 1A, a correct response was recorded only if the RO unit was a correct response value (e.g. Yes or No) from the correct response set (e.g. RO_{Dog}).

5.5.1 Model 1A: Baseline Result

Before reporting the simulation results, it was necessary to ensure that the model could perform the required tasks. To examine this, the initial simulation was run with zero noise. At noise=0, all responses are deterministic and therefore the model should be able to achieve 100% accuracy, which was indeed the case.

The initial model showed comparable RT on Pure and Repetition trials, and longer RT on Switch trials (Fig. 5.6, orange bars). In other words, there was

an RT switch cost but no RT mixing cost. This was due to the fact that both Pure networks and Mixed networks had the same fixed connection weights, resulting in comparable RT. Although we reported no reliable RT mixing costs in the bimodal CMTS experiment, both the unimodal TS experiment and past task-switching studies have generally reported mixing costs. Therefore, it was not clear if the lack of mixing costs in our study was due to factors related to the multisensory environment. As Model 1A focused on task-associated effects, instead of interactions between task-switching and modality-shifting, it was deemed relevant to induce RT mixing costs to begin with, in order to further understand how mixing costs can be modulated by different parameters.

Therefore, to address the issue of a lack of RT difference between pure and repetition trials, all feedforward connection weights in the pure network were strengthened so that processing in the network would be quicker (Fig. 5.6, yellow bars). A quicker and stronger connection from the PS units and the RO units is justifiable since it is foreseeable that translating perceptual information into action should be relatively easy in the pure condition, since there was no task or response ambiguity from the stimulus (at least when cross-modal attentional shift is not considered).

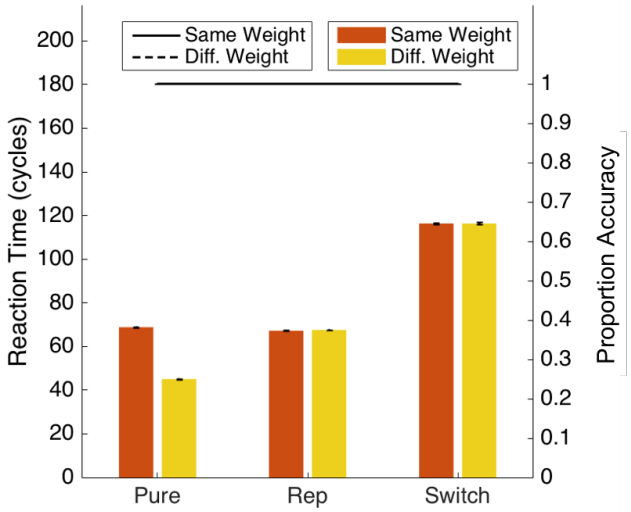

Figure 5.6. Baseline performance of mean RT (cycles) (bars) and Accuracy (lines) at zero noise. Orange bars represent simulations with equal weight settings in pure and mixed networks; Yellow bars represent simulations with stronger PS2RO and TA2RO weights in pure network than in mixed network. Error bars represent 95% CI.

5.5.2 Model 1A Result: Top signal

Having established the architecture for Pure networks and for Mixed networks, I proceeded to explore the effect of the Top signal. In this section, the networks were run with from minimal signal to very strong signal (4 to 40) with a default preparation window (150 cycles). The results are presented in Figure 5.7.

5.5.2.1 Reaction Time

Although a stronger Top signal reduced RT on both pure and repetition trials, the effect was asymptotic beyond a certain level of Top signal. In comparison, modulating the Top signal had a direct and significant effect on the RT on switch trials. Compared to repetition trial, the TA activation on switch trial

was relatively low. We conclude that a significant part of the switch cost has to do with how active the task-relevant TA unit is. Thus, a higher Top signal could reduce the amount of RT switch cost; at a very high signal (Top=40), RT switch costs were effectively eliminated.

5.5.2.2 Accuracy

Accuracy was greater with a higher Top signal on all trial types. Like its effect on RT, the effect of Top strength on accuracy was most evident on switch trials, with an increased Top signal leading to increased accuracy. Nonetheless, even at a very low Top signal (Top=4), the accuracy on switch trials was close to 90%.

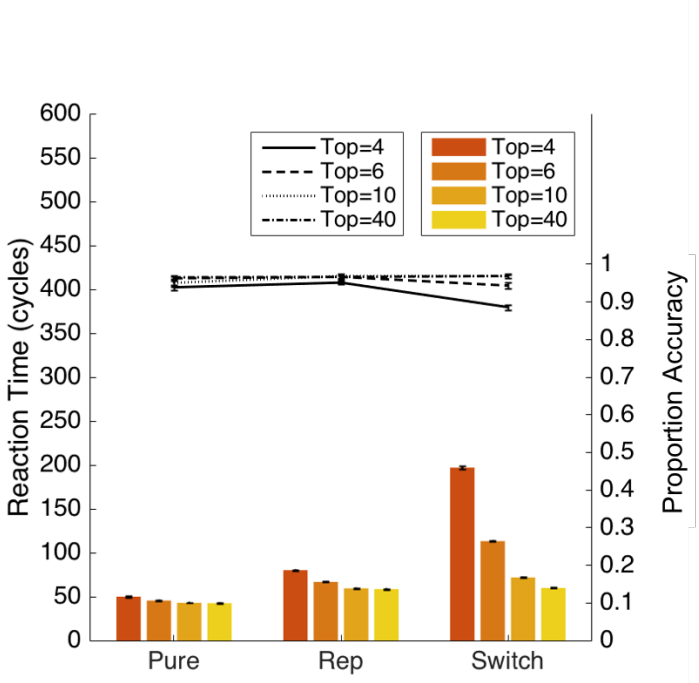

Figure 5.7. Mean RT (cycle) and accuracy on the different trial types (Pure, Repetition and Switch Trial). Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI.

5.5.3 Model 1A Result: Preparation Window

5.5.3.1 Reaction Time.

The models were run with different preparation windows (50 cycles, 150 cycles, 230 cycles and 400 cycles), with a moderate Top signal (Top=6). Longer preparation windows would give the network greater time to excite the task-relevant TA unit. The effect of modulating the preparation window was similar to that of the Top signal as a longer window reduced RT on all trials. On pure and repetition trials, the effect of increasing the preparation window became asymptotic beyond 150 cycles; in contrast, on switch trials, the effect of increasing the preparation window continued even at a very long window (400 cycles) (Fig. 5.8).

5.5.3.2 Accuracy.

Modulating the preparation window had little effect on the accuracy in pure and repetition trials. This is because the task-relevant TA unit was already highly excited at the beginning of the trial and no further update was necessary to ensure a correct task set was selected. In contrast, the accuracy on switch trials was modulated by the preparation window. While the accuracy was greater with a very long preparation window than a reduced one, the differences between the two was not substantial. However, the accuracy fell sharply when the preparation window was very small (50 cycles).

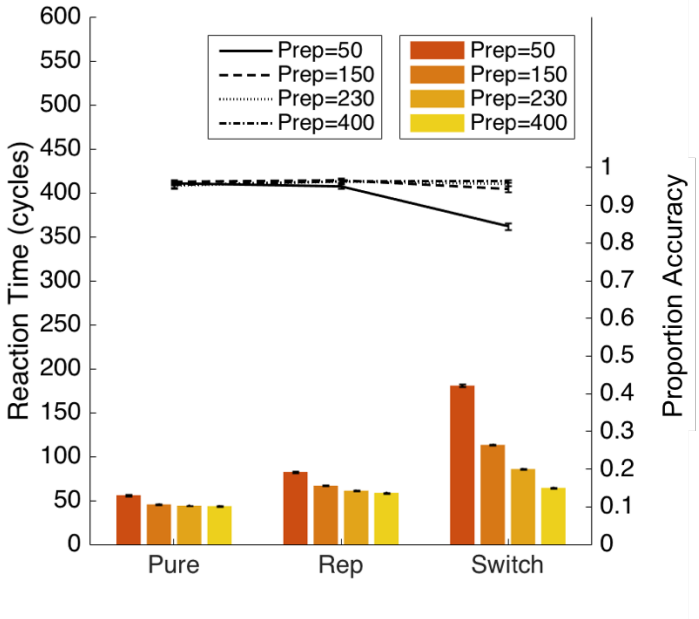

Figure 5.8. Mean RT (cycle) and accuracy on the different trial types (Pure, Repetition and Switch Trial) with different preparation windows (50, 150, 230, 400). Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI.

5.5.4 Model 1A Result: Stimulus-Task Priming

Our behavioural analyses in Chapter 3 explored priming effects with relation to either stimulus-led response-prime in pure and repetition trials (i.e. a trial was considered primed if the two consecutive trials contained stimuli from the same modality and the same target set), or response-led response-prime in switch trials (i.e. a trial was considered primed if two consecutive trials both led to a button-press). The different definition for primes in switch trials was due the fact that a previously responded to target would be a nontarget on switch trial. The behavioural result shows that response-prime had a significant facilitative effect in pure and repetition trials, and a relative (nonsignificant) cost in switch trials (see Fig. 5.9 for behavioural result). This is consistent to past literature on task-switching—a facilitative effect in repetition trials and a cost in switch trials.

Our analyses did not reveal an age effect on the size of priming effects. Note that the priming cost in switch trial was likely to be an underestimate since our behavioural study was unable to index stimulus-led primes on switch trials, due to nonresponses on primed switch trials.

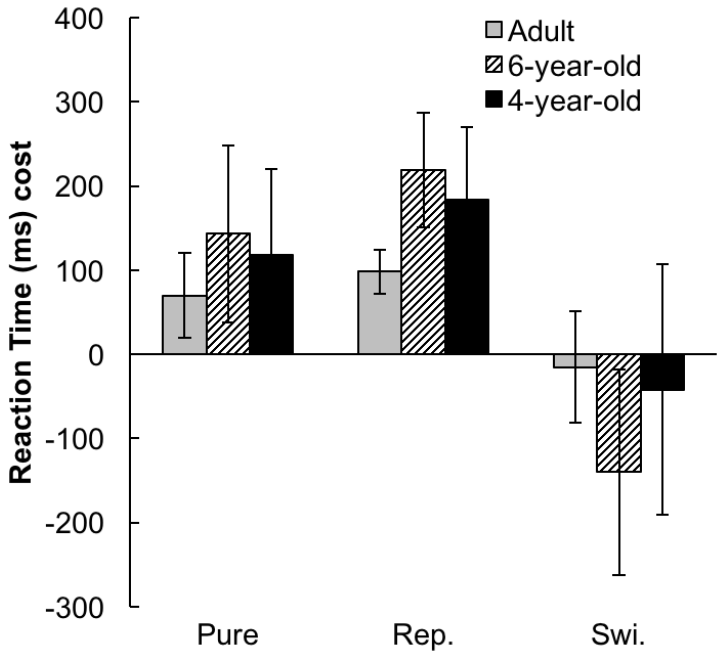

Figure 5.9. RT Priming effect on different trial types in bimodal CMTS behavioural experiment. On pure and repetition trials, the priming effect was stimulus-led (RT differences between unprimed trials and primed trials with the same stimulus category-modality); on switch trials, the priming effect was response-led (RT differences between single response vs. repeated response). Positive values indicate priming facilitation and negative values indicate priming cost. The figure is the same as Fig. 3.4 in Chapter 3.

To explore whether a stimulus-task priming component can capture priming facilitation on pure and repetition trials and priming cost on switch trials, the networks were run with different priming rates.

As described in the network architecture (Section 5.2.2.4), temporary connections are formed between the PS unit(s) and the TA units at the end of each trial (or PS2TA primes). The priming connections are the product between the activation value of the TA units and the PS units on n-1 trial, specified by a fixed learning rate (lrate) that determines the magnitude of the weight changes (see Equation 1). In the current simulation, we varied this learning rate (lrate) as a free parameter. The default networks (preparation=150, Top=6) were run with different priming lrates (0, 1 and 3).

Different priming lrates did not modulate the overall RT and accuracy in any of the trial type (Fig. 5.10). However, when separating the primed and unprimed trials for each trial type, there was a small priming cost on the switch trials; furthermore, the priming cost was larger for greater priming lrates. There was no priming facilitation on pure and repetition trials (Fig. 5.11).

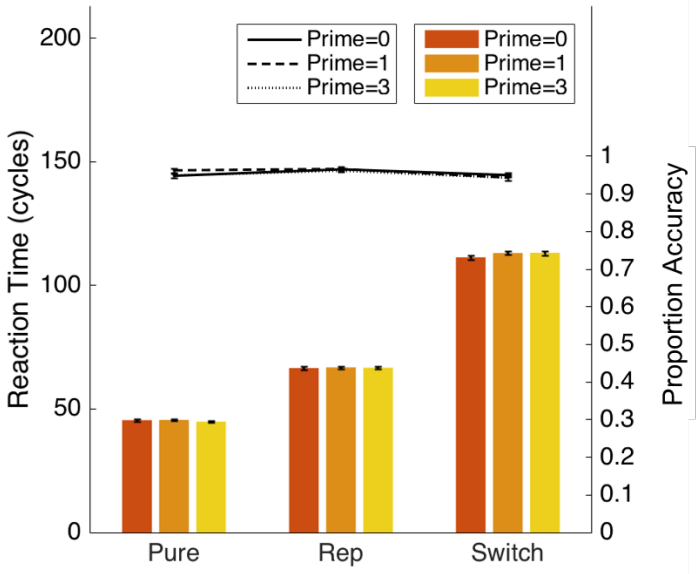

Figure 5.10. Mean RT and Accuracy of different trial types with different priming lrates (no prime=0, moderate prime=1, high prime=3). Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI.

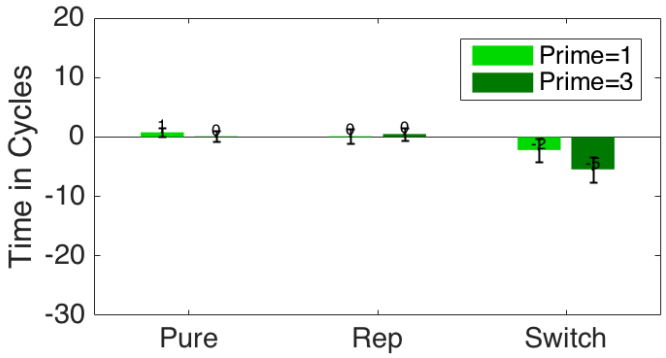

Figure 5.11. Priming effects on different trial types. Bars represent networks run with different PS2TA priming lrates (1, 3). The y-axis shows the RT differences between unprimed trials and primed trials (unprimed - primed). Positive values indicate priming facilitation, while negative values indicate priming cost.

It was also possible that whether a priming effect was observed or not was dependent on the size of the Top signal. Since both priming input and Top input act on TA units, a large Top signal might overshadow the priming effect. It thus follows that if the Top signal was small, the contribution from priming facilitation/interference would be relatively large. To examine this, the model was run with lrate=1 on different Top signals. Indeed, the result showed that when the Top signal was small (Top=4), there was a much larger RT priming cost on switch trials, than with a medium to strong Top signal (Fig. 5.12).

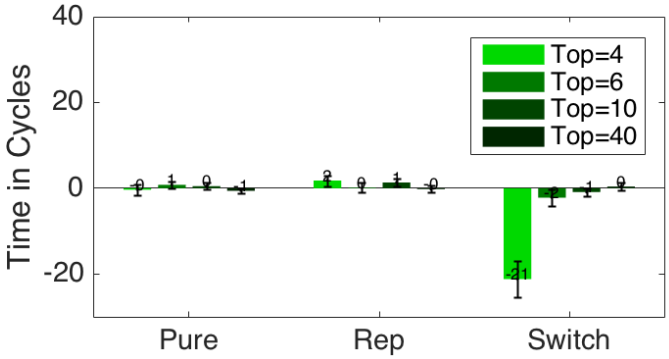

Figure 5.12. Priming effects on networks with different Top signals. Bars represent networks run with different Top signals (4, 6, 10, 40) at prime rate=1. The y-axis shows the RT differences between unprimed trials and primed trials (unprimed - primed). Positive values indicate priming facilitation, while negative values indicate priming cost.

Although the simulations revealed priming costs on switch trials, consistent with past research, they failed to reproduce the facilitative effect of priming on pure and repetition trials. On pure and repetition trials, the TA activations were sufficiently large so there was little facilitative effect from the prime mediated through TA units. It is possible that there are different sources of primes, some of which have a more direct influence on responses. One such prime may be a stimulus-response compound not mediated by task representations.

In the next section, I will further explore how the aforementioned free parameters (Top signal, preparation window and priming lrate) modulate performance in different network ages.

5.7 Model 1B: modelling Age in the networks

In the previous section I have explored how performance on each trial type was affected by Top input, preparation window, and PS2TA primes by running the simulations on a default network. This default network with initial fixed connection weight in Model 1A is adopted as the Old network setting, from which the younger networks are derived with different fixed feedforward weights. It is well documented that children have a slower processing speed than adults (Hale, 1990; Kail, 1991). This age difference in processing speed was modelled by varying the speed of translating perceptual and Top inputs into responses, with a faster speed in older networks than younger networks. To accomplish this, younger networks are assumed to have weaker feedforward connections to the RO units than older networks. Specifically, these connections are TA-RO and PS-RO fixed feedforward connections (see Table 5.1 for weight settings).

All simulations of different network ages (Young, Middle, Old) were run with 25 network subjects, each with the same number of trials as in Model 1A. Unless specified otherwise, the networks were run with standard parameter (Preparation Window=150 cycles, Prime rate=1, Top=6).

5.7.1 Model 1B: Overall performances

As in the previous simulation, different network ages were first run with zero noise to examine if the connection weights are appropriate for the given tasks. All networks were run with the same Top signal (Top=6) and preparation window (150 cycles). The result shows that all networks were able to achieve 100% accuracy when noise was zero, thus confirming the appropriateness of the connection weight settings.

5.7.1.1 Reaction time and accuracy

The networks were subsequently run with noise to examine the performance in a more naturalistic condition. These results are shown in Figure 5.13. Younger networks were slower on all trial types, which is consistent with the behavioural result. Although younger networks showed greater overall RT, they also showed greater overall accuracy. It appears that a slower processing speed (i.e. weaker connection weights) allowed more time for the networks to accumulate appropriate inputs for responses, since the network naturally needs to go through more cycles to settle onto a response. The developmental differences in accuracy differ from the behavioural result, where younger children were overall less accurate.

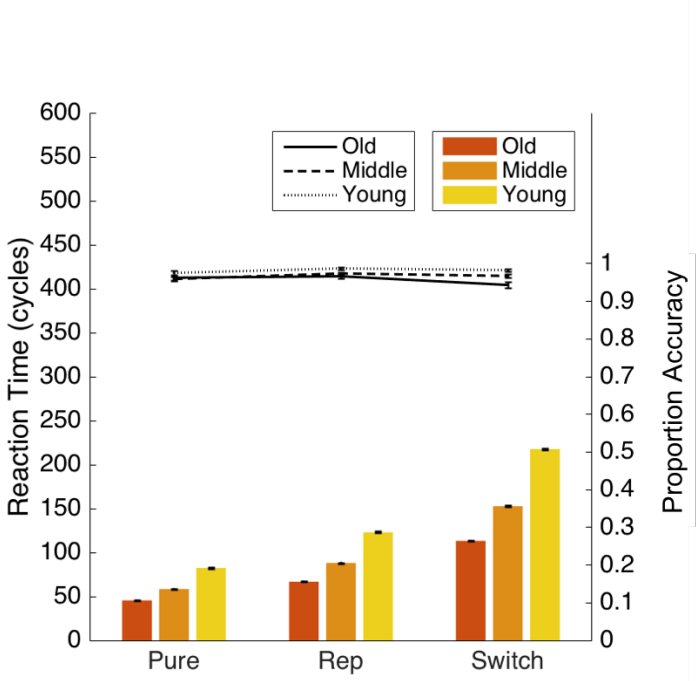

Figure 5.13. Mean RT (cycle) and accuracy on the different trial types (Pure, Repetition and Switch Trial) at different network ages. Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI.

5.7.1.2 RT mixing effect and switch effect

The between-condition differences such as RT mixing cost (repetition vs. pure) and RT switch cost (switch vs. repetition) were also examined (Fig. 5.14). Younger networks showed a greater RT mixing cost and RT switch cost. The developmental effect on the between-condition costs was not consistent with the behavioural result where younger children did not reliably exhibit a larger RT mixing cost or RT switch cost than adults.

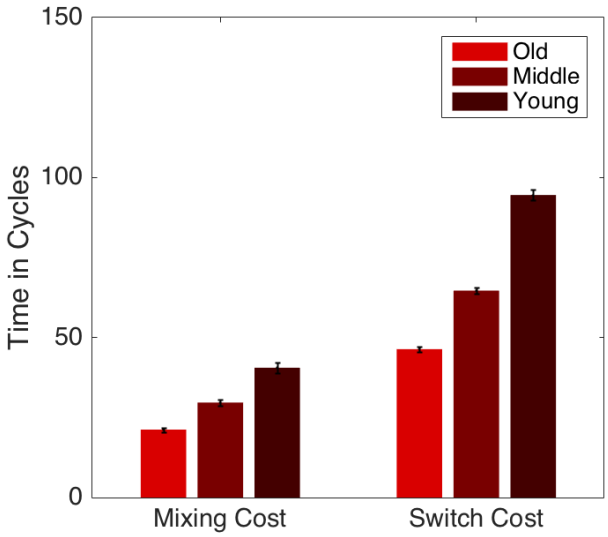

Figure 5.14. RT Mixing Cost (cycle) and RT Switch Cost (cycle) at different network ages—Old, Middle and Young. Error bars represent 95% CI.

5.7.2 Model 1B: Top signal

Networks of all ages were run with increasing Top signals (Fig. 5.15). This had a similar effect across all network ages. Greater Top signals reduced RT on all trials, but the effect was most evident on switch trials. As a result, RT switch costs were smaller with a greater Top signal. Since a very strong Top signal can effectively eliminate the between-condition costs, this may imply that the lack of age effect at the level of between-condition costs observed in the behavioural data was due to younger children employing a stronger Top signal

than older participants. However, this appears unlikely since a stronger Top signal would also improve accuracy and young children were much less accurate than adults in the behavioural experiment.

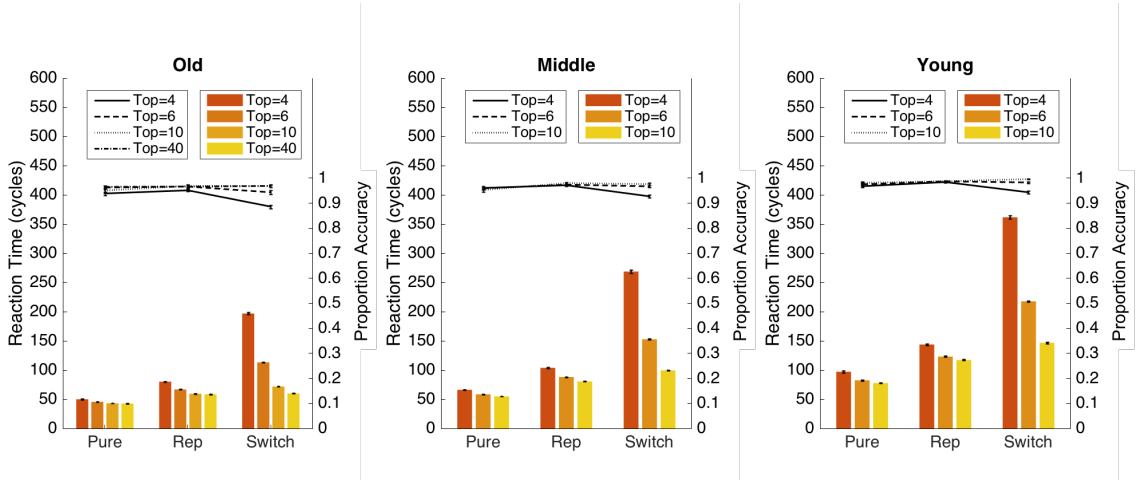

Figure 5.15 Mean RT (cycle) and accuracy in networks with different Top signals. Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI. Left to right: Old, Middle, Young networks.

5.7.3 Stimulus-task priming (PS2TA primes)

The effect of priming on overall performance on each trial type was relatively negligible across all network ages (Fig. 5.16). However, when looking at the priming effects arising from within a condition (i.e. within each trial type), PS2TA primes resulted in RT priming costs on switch trials. A greater priming cost was observed with higher priming lrate, particularly in younger networks (Fig. 5.17). There was no evidence for priming facilitation on pure and repetition trials from PS2TA primes.

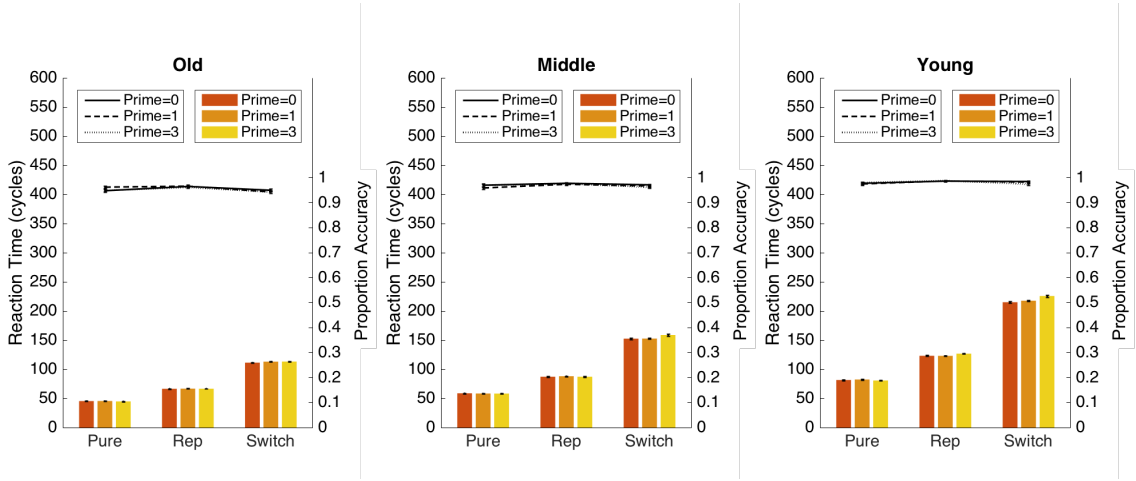

Figure 5.16. Mean RT (cycle) and accuracy in networks with different PS2TA priming rates (0 to 3). Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI. Left to right: Old, Middle, Young networks.

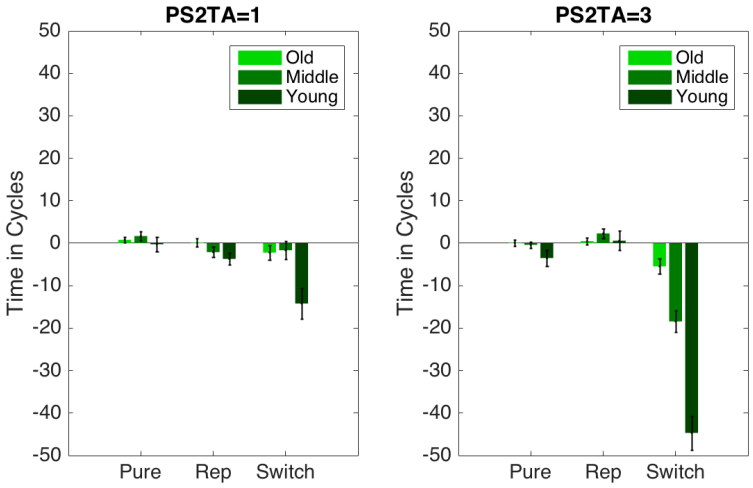

Figure 5.17. Mean priming effects in RT on different trial types in different network ages. Left panel shows networks run with low prime rate (PS2TA prime=1), and right panel shows networks run with high prime rate (PS2TA prime=3). Error bars represent 95% CI.

5.8 General Discussion

Model 1 results suggest that different causes may underlie mixing effects and switch effects. With regards to mixing effects, it appears that the differences in structural setting between the pure and mixed networks (such as connection weights) may account for the effect, rather than competition at the task-set level per se. Since neither Top signals nor duration of preparation window had strong effects on the overall RT and accuracy on pure and repetition trials, mixing costs are unlikely to be caused by factors relating to endogenous control. Instead, differences in the speed of translating representations into responses, through connection weights, may underlie mixing effects. This highlights the possibility that mixing effects may be to do with how the task environment is constructed in the first place, rather than the direct consequence of the interaction among the task-associated elements, such as selection among multiple representations.

In the mixed networks, a greater Top signal and a greater preparation window were both effective at reducing RT on the switch trials. This is done through increasing the activation of the task-relevant TA unit, thereby reducing the competition at the TA level and generating a stronger activation of the appropriate response set. In contrast, Top signal and preparation window had more limited effects on the RTs on pure and repetition trials. This is because, on those trials, the task-relevant TA unit was already excited at the beginning of the trial as activation was carried over from the previous trial.

In sum, RT switch costs were found to be directly associated with factors related to endogenous controls, such as the duration of preparation window and the strength of Top signal. The effect of preparation is consistent with the behavioural finding where a longer window and a transparent task cue reduces

switch costs (Koch, 2003; Logan & Bundesen, 2003; Rogers & Monsell, 1995). An increased Top signal was also effective in reducing RT while improving accuracy. Similarly, a participant with more effective top-down control may therefore need a smaller preparation window to switch task.

The second phase of simulation focused on the effect of free parameters at different network ages. With weaker feedforward connections, younger networks were overall slower on all trial types, consistent with the slower RT(ms) observed in children as compared to adults. However, younger networks also exhibited a greater accuracy than the older networks. This is in stark contrast to the behavioural finding that children were overall less accurate as well as slower. Furthermore, younger networks generally exhibited a larger between-condition RT cost (mixing and switch costs) than older networks. Such developmental differences were not found in the behavioural experiments.

While it is possible to reduce the age effect on between-condition costs by eliminating the overall switch cost and mixing cost through a very high Top signal, to do so would also go against the common belief that children were overall less efficient in top-down control than adults. Furthermore, a high Top signal would also result in higher accuracy on switch trials, since it would ensure the correct response set was chosen. Although children in our experiments did not exhibit greater between-condition processing costs (mixing and switch costs), they nonetheless exhibited lower overall accuracy on all trial types. A high Top signal would not be consistent with our behavioural findings. It is likely that other mechanisms are at play in reducing the effect of age on RT switch cost.

Although the general network behaviours were similar in both young and older networks, younger networks were more susceptible to priming costs due

to PS2RO primes on switch trials. The greater RT priming costs are likely to be due to the slower baseline speed in Young and Middle networks. This is because a slower network also means that the primes would go through a greater number of cycles during response setting and selection. In comparison, the simulations did not uncover any priming facilitation on pure and repetition trials, indicating that goal-mediated stimulus-task attribute primes did not further promote response setting when the task goal was already highly activated.

There was also a floor effect in Model, as all networks were resistant to errors, despite the occasional errors under extreme conditions on switch trials (i.e. very low Top signal or very low preparation window). Counterintuitively, younger networks were more accurate than older networks in Model 1. In the behavioural experiment, only adults were at ceiling performance across all trial types, younger children, particularly 4-year-olds, made far greater number of errors than adult participants, including the 'easy' repetition trials. Model 1 was unable to capture the developmental differences in accuracy.

In summary, Model 1 was able to capture aspects of between-condition RT costs: (1) RT mixing costs may reflect different underlying assumptions in information processes. The associative strengths between different representations may be stronger in pure condition than in mixed condition, despite the stimuli and responses share perceptual and motoric similarities in the two conditions, and (2) RT switch costs are directly associated with the parameters that relate to endogenous control, such as preparation window and Top signal. Therefore, RT switch costs may be a valid measure of cognitive control in switching tasks, at least when the accuracy is high (e.g. >90%). Model 1 was also able to capture some developmental differences: (3) Younger networks were slower than older networks due to weaker feedforward

connection weights, which determine the baseline speed of a network. (4) Younger networks with weaker connections experienced greater RT priming costs from PS2TA primes, which is consistent with the past study demonstrating a greater automatic priming effects in children than adults (Ridderinkhof et al., 1997; Smulders et al., 2005).

However, Model 1 was unable to capture other notable behavioural findings in bimodal CMTS—namely: (1) the lack of developmental differences in between-condition RT costs, and (2) priming facilitation in pure and repetition trials. Furthermore, (3) Model 1 shows a strong floor effect on accuracy in pure and repetition trials, and a smaller floor effect on switch trials. Thus, Model 1, with its relatively simple architecture, cannot capture the developmental differences in accuracy observed in children and adults.

In Chapter 6, I will introduce additional connections to the existing Model 1 and investigate how performance changes when TA units can be activated reactively, and how RT priming facilitation may be due to reactive primes that are not associated to task attributes. Past literature suggests that young children are more likely to respond reactively to perceptual information, and it is possible that these reactive processes specific to our experiment masked the developmental effect on between-condition costs (e.g. mixing or switch costs) in the bimodal CMTS study.

Table 5.1 Parameter setting in Model 1

Parameter Name	Old /Default	Middle	Young
Weights (Pure networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
TA unit to RO_{YES} unit	3.8	3.4	3.0
TA unit to RO_{NO} unit	2.8	2.4	2.0
Lateral connections from RO_{YES} to RO_{NO}	-1.3	-[1]	-
Lateral connections from RO_{NO} to RO_{YES}	-1.0	-	-
Weights (Mixed networks)			
PS_{VIS} unit to RO unit	2.7	2.3	1.9
PS_{AUD} unit to RO unit	2.5	2.1	1.7
TA unit to RO_{YES} unit	2.8	2.4	2.0
TA unit to RO_{NO} unit	1.8	1.4	1.0
Within-set lateral connection from RO_{YES} to RO_{NO}	-1.3	-	-
Within-set connection from RO_{NO} to RO_{YES}	-1.0	-	-
Between-set lateral connections between RO_{Dog} and RO_{Bird}	-1.3	-	-
Inputs			
Top signal	4 to 40	4 to 10	4 to 10
PS units (clamped activation)	1	-	-
Bias	-3	-	-
Time constraints			
Preparation window	150	-	-
Timeout	600	-	-
Other parameters			
Priming lrate between PS and TA [Eq. 1 in Chapter 5]	1 to 3	-	-
Step size [Equation 4&5 in Chapter 5]	0.0015	-	-
Noise[2]	0.006	-	-
Response threshold	0.2	-	-
Min. and max. activation of TA and RO units	-1.0 to 1.0	-	-
Squashing parameter for TA	0.7	-	-

1. The symbol '-' indicates that the setting is the same as in Old network

2. The number is the standard deviation of a normal distribution with a mean of 0, which is used to produce a random noise added to each unit activation update.

Chapter 6. Reactive Mechanisms (Model 2)

Model 2 [1] investigates different types of reactive mechanisms. Specifically, the simulations presented in this chapter aim to understand how task representations can be triggered reactively (Model 2A, *Reactive Task Retrieval*), as well as how responses can be committed reactively through priming pathways (Model 2B, *Reactive Responses*). As was the case in the previous chapter, the models in this chapter only explored task-associated effects.

6.1 Model 2A: Reactive Task Retrieval

Younger children are more likely to switch mental representations reactively after detecting change signals, whereas older children and adults are more likely to utilise informative cues in advance of the stimulus onset (Chevalier et al., 2015; Doebel et al., 2017; Morton & Munakata, 2002). For example, transparent task cues have been shown to be particularly helpful for young children, as compared to arbitrary task cues (Blaye & Chevalier, 2011). This may be due to the fact that a task can be triggered more reactively when the task relevant information is already present in the transparent (i.e. strongly associated) task cue. In our behavioural experiments, both cues and stimuli were fairly transparent and strongly associated with the task attributes (e.g. animal categories). Thus, it is likely that both did the task cue, and the stimuli (e.g. seeing the 'Dog' stimulus reminded the participant to engage in the 'Dog'

[1] All parameters setting used in the simulations in Chapter 6 are listed in Table 6.1 at the end of chapter.

task) activated the task attribute. Younger participants may have relied more on this reactive task set trigger than adults.

Therefore, Model 2A explores possible mechanisms that activate task attributes other than the Top signal. In particular, Model 2A investigated whether young networks benefit from reactive activation of task attribute representations, even when their Top signal was relatively low. Specifically, we aimed to understand whether reactive task retrieval can be effective in reducing RT switch costs in younger networks.

In the next section, I will begin by describing the architecture of Model 2A in detail.

6.1.1 Model 2A: PS to TA Reactive Pathway

To model the reactive associations that exist between task representation and the percept stimulus, additional fixed feedforward connections between PS units and the associated TA units are introduced in Model 2A (e.g. DV and DA to TA_{DOG}, BA and BV to TA_{BIRD}, see Fig. 6.1). The additional connections are not expected to have an effect on pure trials since there is only one TA unit. On switch trials in the mixed networks, the *PS-TA* connections should be facilitative in activating the task-relevant TA unit when the target is present, especially when the Top signal is small, but it can also introduce competition when a nontarget is present on the switch trial. On repetition trials, the cost/benefit may be more limited since the task-relevant TA unit is likely to be highly excited and the task-irrelevant TA unit highly inhibited. Unlike other fixed feedforward connections where there are developmental differences in connection weights, due to the reactive nature of the processes, the PS-TA connections are the same across all network ages.

There are additional assumptions built into Model 2A with regards to the developmental differences between networks. It is assumed that younger networks will have smaller (but sufficient) overall Top signal than older networks (Top_{Old}=10, Top_{Middle}=7, Top_{Young}=5). Finally, in this section, there were 25 network subjects of each network age. The number of trials was the same as in Model 1 (Chapter 5), and the targets appeared with 60% probability.

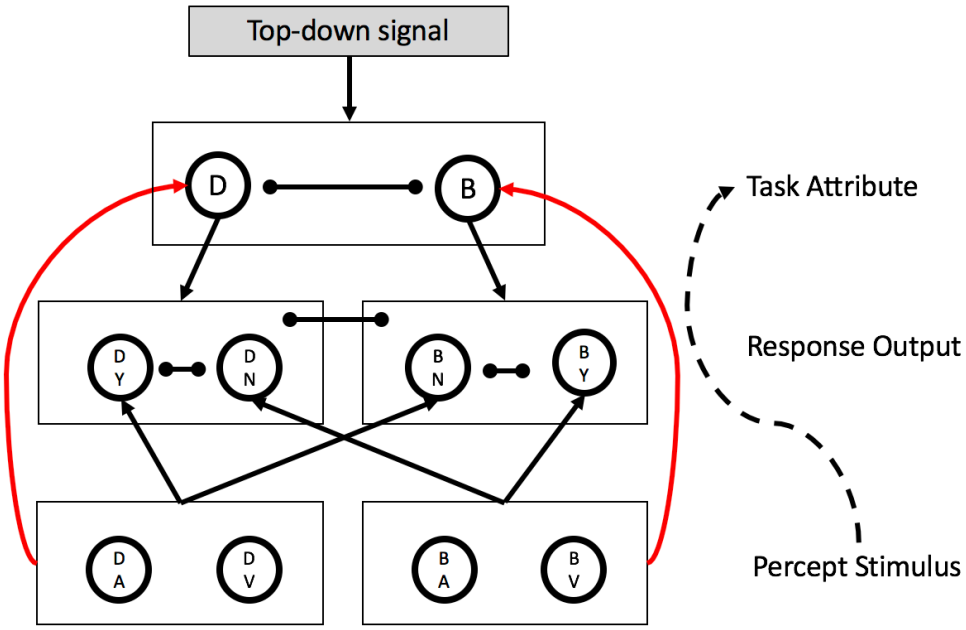

Figure 6.1. Model 2A Architecture with additional Percept Stimulus to Task Attribute feedforward connections (PS-TA). The new connection from the previous model is highlighted in red.

6.1.2 Model 2A: Result

6.1.2.1 Reaction time and accuracy

The additional PS-TA connections in Model 2A reduced the RT on switch trials at all network ages, as compared to networks without the PS-TA connections (see Fig. 6.2). As expected, the PS-TA connections had no effect

on overall RT and accuracy on pure and repetition trials in any of the network ages. This is due to the strong existing TA activation on pure and repetition trials, so the additional input from the PS-TA reactive pathway adds little to the settling process.

On switch trials, there was a reduction of RT in Middle and Young networks, but not in Old networks. As the Top signals were smaller in Middle and Young networks, the relative contribution from PS-TA inputs was larger in these networks, as compared to Old networks. However, their faster responses on switch trials was accompanied by a reduction in accuracy on switch trials, indicating that relying on the bottom-up activation of task representation is not the optimal task approach.

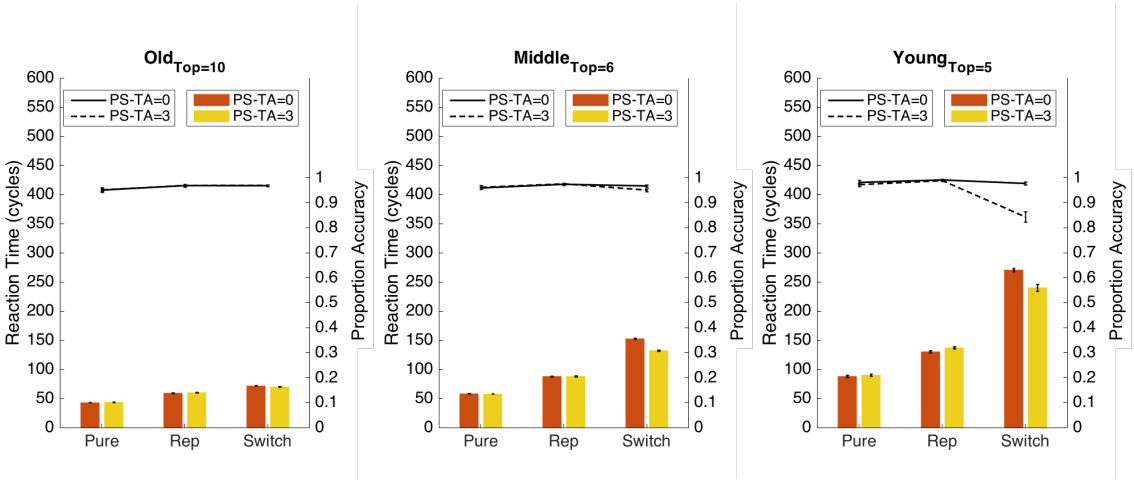

Figure 6.2. Mean RT and accuracy in with and without PS-TA reactive pathways across different network ages. Orange bars show networks without PS-TA pathways, and yellow bars show networks with PS-TA pathways. Left to right: Old, Middle and Young networks. Error bars represent 95% CI of means.

6.1.2.2 Between-condition RT costs

Without the PS to TA reactive connections, the developmental differences in RT switch costs were fairly substantial. The additional PS to TA connections reduced RT on switch trials in the younger networks, thereby

reducing the developmental differences in switch costs (Fig. 6.3). However, the reactive pathway did not eliminate the effect of development on RT switch costs.

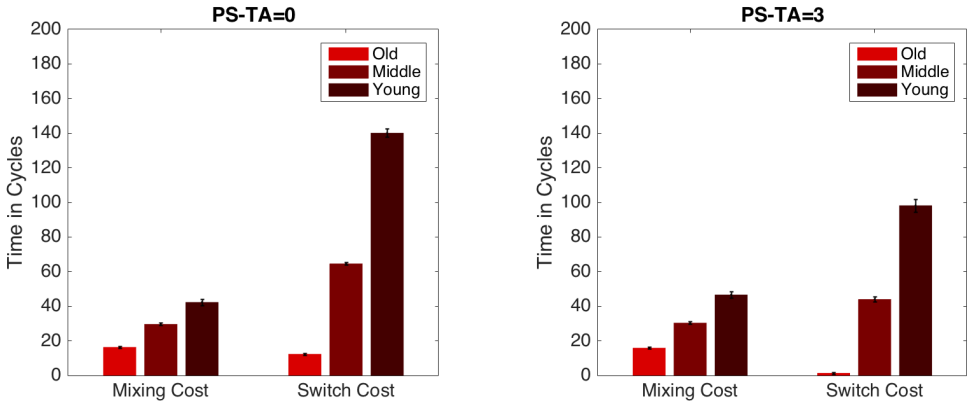

Figure 6.3 Mean RT Mixing Cost and RT Switch Cost. Left panel shows costs in networks without PS-TA connections; right panel shows costs in networks with PS-TA connections (weight=3). Different bars represent different network ages. Error bars represent 95% CI of means.

6.1.3. Model 2A: Discussion

Model 2A simulations explored the idea that task attribute representations can be reactively activated upon seeing the stimulus, as well as through an internal biasing mechanism such as Top signals. The reactive pathway through PS-TA connections can be both facilitative of and obstructive to task performance. The facilitative effect was observed with smaller RT on switch trials with PS-TA connections than those without, particularly when the Top signal was small. However, PS-TA input can also have a detrimental effect on accuracy. The accuracy cost was caused by the inability of the Top signal to override the reactive signal when the task-irrelevant target was present.

To model the effect of development, we made a few assumptions in terms of the Top signals of different network ages. Older networks were assumed to have more efficient top-down control, thus a stronger Top signal than younger networks. With these additional assumptions, it was found that both Middle and Young networks benefited from the additional PS-TA input on switch trials, showing faster responses on switch trials. In contrast, Old networks (i.e. larger Top input) did not display such a benefit.

Model 2A was able to reduce RT switch costs and induced errors on switch trials in Middle and Young networks. This model was therefore an improvement from Model 1 (Chapter 5). However, despite these improvements, the limitations in Model 1 remained in Model 2A; namely, the reversed developmental effect on RT switch costs and the floor effects on accuracy in all trial types.

In the next section, we will consider another reactive mechanism—namely, reactive primed responses.

6.2 Model 2B: Reactive Reponses

6.2.1. Model 2B: Stimulus-response primes

In Model 1 (Chapter 5), we saw that PS2TA (stimulus-task) primes resulted in processing costs on switch trials, but that this priming mechanism could not account for the facilitative effect observed in the pure and repetition trials of our behavioural experiment. In our bimodal CMTS study, there was strong priming facilitation in these two types of trials, particularly in children (Fig. 5.8, Chapter 5). It is possible that priming facilitation was not mediated by task attributes (i.e. TA units); instead, perhaps the response was directly associated with the stimulus on the n-1 trial. Therefore, Model 2B will explore the effect of

stimulus-response (*PS2RO*) primes on response facilitation in pure and repetition trials, in addition to the strong reactive task retrieval pathway (PS-TA=3).

To model this effect, temporary connections were formed between PS unit(s) and the RO units at the end of the trial (PS2RO, see Figure 6.4 for the network architecture). Thus, in Model 2B, PS unit(s) would send inputs to the RO units directly through temporary priming connections, and this priming effect would not be mediated by task representation.

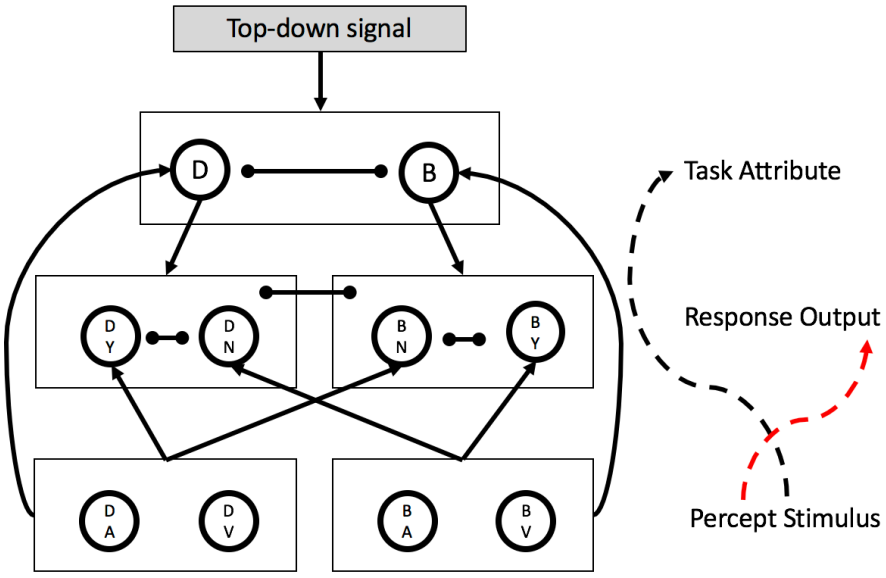

Figure 6.4. Model 2B Architecture with additional PS-RO priming connections in mixed networks. The new connection from the previous model is highlighted in red.

Like the PS2TA primes, the PS2RO primes only lasted for one trial, and had the same governing equation used for PS2TA primes (Eq. 1, Section 5.2.2). It is important to note that like PS2TA primes, PS2RO connections can be positive or negative, since all RO units (both excited and inhibited units) form temporary connections with the PS unit(s). On pure and repetition trials, PS2RO primes are most likely to result in response facilitation. On switch trials, since

the correct response is always different from the correct response in the n-1 repetition trial (i.e. different response set), PS2RO primes are most likely to induce an additional cost. However, it is not clear whether the cost will be exhibited in RT and/or accuracy.

As with Model 2A, older networks have greater fixed feedforward connection weights and Top signals than younger networks. Model 2B was run with different priming rates at each network age. The trial number and preparation window were the same as in Model 2A.

6.2.2. Model 2B: Results

6.2.2.1 Reaction Time and Accuracy

Figure 6.5 shows the between-condition effect of priming effects on different trial types by overall accuracy and RT at different network ages. Although there was a slight decrease in the overall RT on pure and repetition trials in all network ages, the addition of PS2RO primes on top of the existing PS2TA primes did not have a strong effect on the overall RT at any network age.

Model 2B showed slightly greater variances than Model 2A in accuracy on pure and repetition trials,. This may be due to the fact that network behaviours are more volatile with increasing numbers of parallel processes. Despite this, accuracies on pure and repetition trials were overall similar to those in previous models.

The accuracy on switch trials varied by PS2RO priming lrate and network age. The accuracy in Old networks did not change with priming lrate, indicating that the networks were overall resistant to priming interference. In contrast, both Middle and Young networks showed a gradual decrease in accuracy with increased PS2RO priming lrate. The rate accuracy reduction was greater in

Young than in Middle networks, indicating that Middle networks were slightly more resistant to priming interference than Young networks.

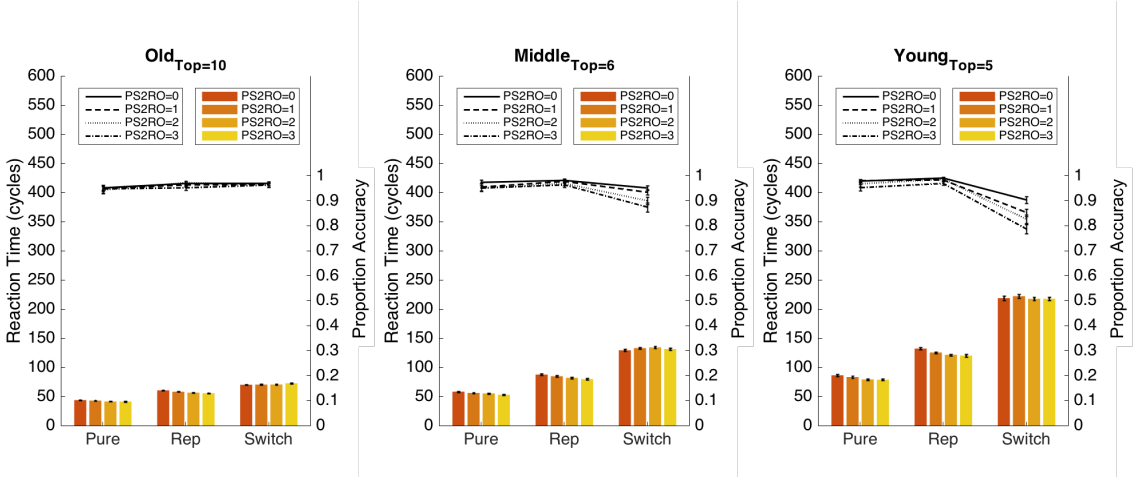

Figure 6.5. Mean RT and Accuracy to different trial types with different PS2RO prime rates (1, 2, 3). Left to right: Old, Middle, Young networks. All networks were run with a strong reactive task retrieval (PS-TA=3). Error bars represent 95% CI of means.

6.2.2.2 Priming Effect

The priming effect was also examined with within-condition comparisons. This was achieved by taking the RT difference between unprimed and primed trials within each trial type (Fig. 6.6), and comparing it to the behavioural finding (Fig.6.7). It was hypothesised that the introduction of PS2RO primes would produce a facilitative effect on pure and repetition trials. The simulation results confirmed the presence of priming facilitations on pure and repetition trials, and priming costs on switch trials. Furthermore, a larger priming lrate resulted in greater RT facilitation on pure and repetition trials across all network ages. The younger networks exhibited greater RT facilitation from PS2RO primes than the older networks, as indicated by the larger RT differences between primed and unprimed trials.

There were priming costs on switch trials, across all network ages. However, the relation between the size of the priming costs and priming lrate is

less consistent across different network ages. It is therefore possible that some of the priming costs in the younger networks were translated into accuracy costs instead.

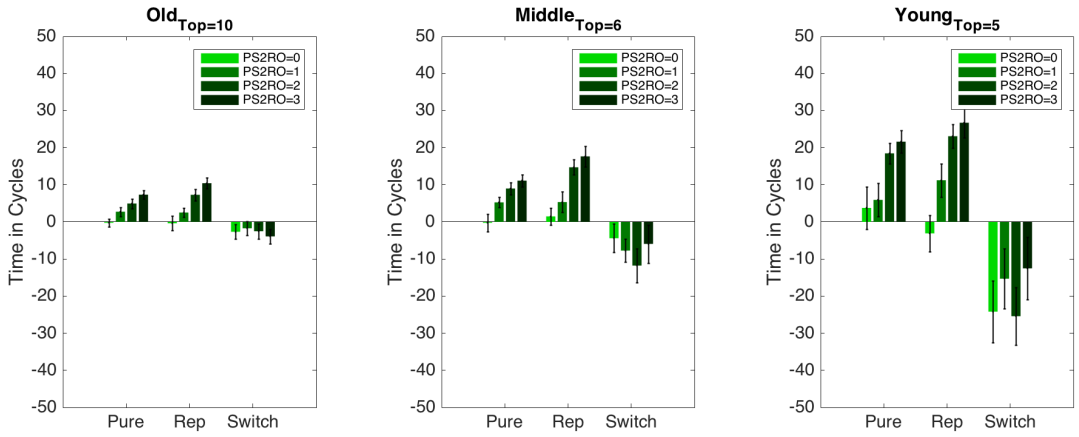

Figure 6.6 Mean priming effects in RT on different trial types. The bars represent networks with different prime rates (0 to 3). The y-axis shows the RT(cycle) difference between unprimed trials and primed trials (unprimed - primed). Positive values indicate priming facilitation; negative values indicate priming cost. Left to right: Old, Middle, Young networks. Error bars represent 95% CI of means.

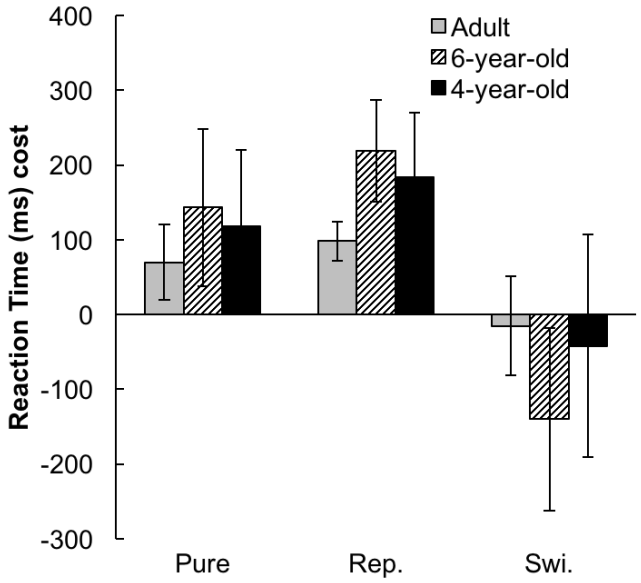

Figure 6.7 RT Priming effect on different trial types in bimodal CMTS behavioural experiment. The figure is also shown in Chapter 5 (Fig. 5.9). Error bars represent 95% CI of means.

6.2.3 Model 2B: Discussion

Model 2B was successful at capturing the facilitative effect of stimulus primes, through the priming connections between stimulus and response. Priming appears to have a larger effect in the younger networks than the older networks. In Old networks, the strong Top signal meant that the networks would always select the correct response set, despite interferences from reactive primes. In contrast, Middle and Young networks had smaller Top signal and therefore they were more likely to make incorrect responses when the effect from reactive response primes were strong.

While the Top signal determined whether reactive response primes would result in accuracy cost, network age differences in baseline speed determined the size of priming facilitation on pure and repetition trials. Since

PS2RO primes had direct input into RO units, the RT facilitative effect stemmed from the elevated baseline activation of the RO unit in reaching threshold on primed trials, as compared to unprimed trials. This RT facilitation was stronger in a younger network than an older network due to the relatively larger proportional gain in baseline activation in a slower network than a faster network (Fig. 6.8).

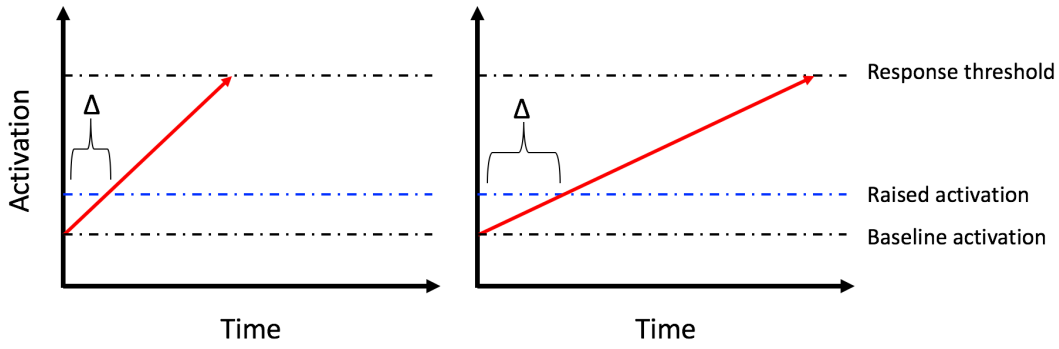

Figure 6.8 Schematic illustration of speed facilitation (Δ Time) with a raised baseline activation in a fast (left) and slow (right) activation accumulator.

The simulation results thus confirm that priming associations could exist among different elements within the task structure (e.g. PS2TA and PS2RO, although other associations may exist), and that performance could be different depending on how the associative compounds were formed. Unlike PS2TA primes, PS2RO primes were able to modulate accuracy on the switch trials, highlighting that different types of priming effects may be manifested in different measures.

6.3 Model 2: General Discussion

The models in this chapter explored the possibility that younger children did not exhibit greater processing costs due to the facilitation from other reactive processes. Model 2A investigated the effect of reactive task retrieval by

introducing a parallel processing connection from PS units to their corresponding TA units after stimulus onset. The effect of reactive task retrieval was stronger for younger networks than old networks, as only Middle and Young networks exhibited a reduction in RT on switch trials; however, this speed facilitation was also accompanied by an increase in error.

The other reactive pathway consisted of the reactive response primes (PS2RO). Unlike the reactive task retrieval pathway, where the speed facilitation was only evident on switch trials, the reactive stimulus-response primes had speed facilitation effects on both pure and repetition trials, but the effects were very small. As for reactive task retrieval, reactive response primes resulted in decreased accuracy on switch trials, with a larger effect in a younger than an older network. Model 2B also showed that stimulus-response speed facilitation was larger in a younger network than an older network, due to differences in the baseline processing speed at these different ages.

Although these reactive pathways could reduce overall RT on different trial types, they nonetheless did not eliminate the effect of age on between-condition RT mixing and RT switch costs. In addition, the strong floor effect on accuracy in pure and repetition trials remained unchanged in Model 2. On pure and repetition trials, the task-relevant TA units were consistently excited across the duration of the trial. As a result, there was little room for the network to make errors since it would always choose the correct response set.

Lacking other dynamic functions that can produce stochasticity in network performance, Model 2 was unable to capture the developmental differences observed in accuracy. It is also possible that the lack of developmental differences in between-condition measures (e.g. mixing and switch costs) has to do with the variation in baseline performance on pure and

repetition trials. As long as these variations are not captured by the model, it is not possible to explain why young children exhibited comparable between-condition costs as adults. Therefore, models with stochastic functions that modulate the performance on pure and repetition trials may shed light onto the paradoxical phenomenon of lower overall performance in children and the absence of developmental effect on mixing and switch costs. This will be explored in the next chapter.

Table 6.1 Parameter setting in Model 2

Parameter Name	Old	Middle	Young
Weights (Pure networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
TA unit to RO_{YES} unit	3.8	3.4	3.0
TA unit to RO_{NO} unit	2.8	2.4	2.0
PS unit to TA unit*	0 or 3	-	-
Lateral connections from RO_{YES} to RO_{NO}	-1.3	-	-
Lateral connections from RO_{NO} to RO_{YES}	-1.0	-	-
Weights (Mixed networks)			
PS_{VIS} unit to RO unit	2.7	2.3	1.9
PS_{AUD} unit to RO unit	2.5	2.1	1.7
TA unit to RO_{YES} unit	2.8	2.4	2.0
TA unit to RO_{NO} unit	1.8	1.4	1.0
PS unit to TA unit*	3	-	-
Within-set lateral connection from RO_{YES} to RO_{NO}	-1.3	-	-
Within-set connection from RO_{NO} to RO_{YES}	-1.0	-	-
Between-set lateral connections between RO_{Dog} and RO_{Bird}	-1.3	-	-
Inputs			
Top signal	10	6	5
PS units (clamped activation)	1	-	-
Bias	-3	-	-
Time constraints			
Preparation window	150	-	-
Timeout	600	-	-
Other parameters			
Priming lrate between PS and TA	1	-	-
Priming lrate between TA and RO*	0 to 3	-	-
Step size	0.0015	-	-
Noise	0.006	-	-
Response threshold	0.2	-	-
Min. and max. activation of TA and RO units	-1.0 to 1.0	-	-
Squashing parameter for TA unit	0.7	-	-

* Indicates new parameter in the current chapter.

'-' indicates the same setting as in Old networks.

Chapter 7. Population-wide dynamic cognitive control (Model 3)

Models 1 and 2 have explored how task performance can be affected by different internal (e.g. Top signal) and external (e.g. preparation window) free parameters, as well as by variations in the trial-by-trial activation dynamics (e.g. priming effects). Despite some success in capturing accuracy variations on switch trials at different network ages, performance on pure and repetition trials remained largely unchanged with different parameter settings. Since mixing effects and switch effects are measured in relation to either pure or repetition trials, to account for between-condition costs across different ages, it is imperative to have a model that captures performance on these control trials well.

Task performance in the simulations was largely dependent on the model selecting the appropriate task-relevant response set (i.e., activating the correct TA unit). The main reason for the stability of the model's performance in pure and repetition trials is that the TA units remained highly excited/inhibited throughout the trials. However, in real life, task representations may wax and wane, particularly when attention is engaged in other cognitive and perceptual processes. Thus, on repetition trials, it is possible that the participants made errors due to a failure in maintaining the appropriate task-relevant representation.

The models [1] presented in Chapter 7 explore different dynamic mechanisms that may also modulate the task representations in the behavioural studies. A series of computational models was developed, with the specific aim of understanding the mechanisms that affect performances at the inter-group, inter-individual, and intra-individual levels.

7.1 Introduction

7.1.1 Overview of mixed networks

On repetition trial in Models 1 and 2 (Chapters 5 and 6), as the task-relevant TA unit is always activated and the task-irrelevant TA unit inhibited, unsurprisingly, the networks always chose the correct response set. In addition to the stability provided at the TA level, there was additional facilitation from the n-1 primes, both at the task attribute level and at the response level. One way to overcome this consistent activation at the TA level is to introduce a decay function. Specifically, the decay function should allow TA units to lose strength and gravitate towards a neutral state (i.e. '0' that is neither excited nor inhibited).

To allow the decay function to work, it is necessary that the Top signal be intermittent during the response settling process (Fig. 7.1, left network). The idea of intermittent top-down control is consistent with the finding that task representation are likely to partially rely on intermittent verbal rehearsal of the task rules (Kray et al., 2008, 2004). The probability of a top-down update occurring may be a matter of inter-individual difference. Some participants may be more likely than others to engage in verbal task rehearsal than others, and

[1] All parameters setting used in the simulations in Chapter 7 are listed in Table 7.3 at the end of chapter.

thus exhibit *individual differences* in task performance within an age group. Simulating each network age with systematically different update probabilities allows us to understand how these individual differences play out on different trial types within the age group, and thus allows us to appreciate population-wide performance variations. Model 3A specifically investigates the effect of update probability on performance at different network ages.

In Model 3B, we go back to explore the effect of Top signal strengths in different network ages. The procedure here is similar to that used with Model 1B in which I varied the strength of the Top signal systematically. The difference between Model 1B and Model 3B is that, in Model 3B the networks involved TA decay and were run using a *population approach* whereas the networks in Model 1B were run with identical networks within each network age. The population approach involves creating a sample of networks with different update probabilities as proxy for individual differences. For example, network subject A may be more likely to update task goal than network subject B (e.g. 30% vs. 60%), despite both networks belonging to the same network age. The result in Model 3B was used to inform the possible range of performance variations at each network age with a more realistic sample of network subjects.

Model 3C further explores the range of task strategies a specific age was most likely to employ, through replicating the accuracies on each trial type. This is based on the assumption that top-down control is unlikely to be static across the duration of the experiment, but is modulated by participants' understanding of the overall task demand and motivations. Specifically, the strength of top-down control could not only differ with development, but could also be modulated by trial type. Several researchers have proposed the differentiation between a proactive versus a reactive task approaches (e.g., Braver, 2012;

Cragg & Chevalier, 2012; Doebel et al., 2017). These different approaches are likely to reflect a combination of developmental constraints and task strategies. In Model 3C, I will examine the most likely task strategy employed by different age groups, and attempt to shed light on the paradoxical observation of lower overall accuracy yet no reliable between-condition costs observed in the behavioural studies.

7.1.2 Overview of pure networks

The pure networks in Models 1 and 2 are similar to mixed networks in that both have a higher level task attribute representation. The inclusion of a task attribute unit was effective in speeding up responses in pure networks because the RO units received multiple inputs. However, without the TA unit, the task could still be successfully carried out by simple stimulus-response associations. Although Model 2 (Chapter 6) produced some errors, the number of errors was negligible. In the behavioural experiment, younger participants produced more errors than the older participants. This is an important dimension of the behaviour that needs to be captured.

One potential explanation might be that younger children did not form a task representation, unlike the older participants who did form such a representation, since the bottom-up information was sufficient to complete the task. However, they still committed a large number of errors in the pure blocks. Forming a task representation is likely to lead to better on-task performance. Indeed, without a task representation, the resulting bottom-up approach may be more vulnerable to internal and external task-irrelevant intrusions that have a negative effect on behaviour. This scenario may be more likely to occur in the pure condition than the mixed condition. This is because the participants might

be more likely to actively form task goals if they are imperative for successful task performance. In the mixed condition, goal representations are necessary in order to achieve high accuracies. In contrast, the participants might not actively from task goals in the pure condition because these are not an imperative element in the overall task structure.

In Model 3, I explore how pure networks perform when there is no task attribute in the model architecture. In the computational model, instead of serving as a facilitator for task performance, the internal input (i.e. the Top signal) may instead cause interference because it does not act upon a higher level representation. Without a TA unit, pure networks have network architectures that differ fundamentally from those of the mixed networks. According to this view, the mixing costs observed in the behavioural experiments may reflect fundamental differences in information processes between pure and mixed tasks. For these reasons, the performance variation in the pure trials is of interest on its own.

In this chapter, all network in the pure condition were simulated without TA units (Fig. 7.1, right network). Instead, internal signals were sent directly to the RO units, with a stronger signal to RO 'YES' and a weaker signal to RO 'NO' to reflect a bias towards pressing the "YES" response button. To differentiate between the Top signals to TA units in the mixed networks and the internal interference in the pure network, I will refer to the signal in the pure network as the '*Intrinsic signal*'.

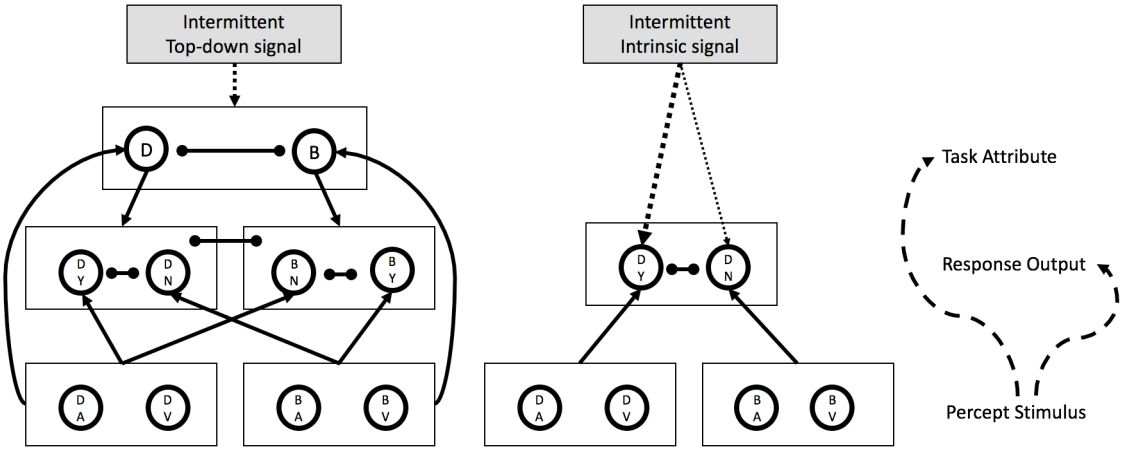

Figure 7.1. Model 3 Architecture with intermittent (dashed lines) Top and Intrinsic signal in mixed (left) and pure (right) networks, respectively. Note that in the pure network there is no task attribute layer. The right-most graph illustrates PS2RO and PS2TA priming connections.

7.2 Model 3A: Update probability

In this section, I will focus on Model 3A, which explores the effect of different update probabilities of the Top signal after the preparation window. These update probabilities are assumed to reflect inter-network differences within each network age, and therefore individual differences within an age in the experiment.

7.2.1 Model 3A: Basic assumptions

Update probability refers to the probability of Top/Intrinsic signal sending activation on a particular update cycle. For example, at 10% update probability, a Top/Intrinsic signal occurs with 10% probability during the response settling process. In mixed networks, update probability is assumed to reflect inter-individual differences (as opposed to inter-group differences such as age) in the likelihood of engaging with self-reminders. In the behavioural experiment, many

4-year-olds appeared to understand the utility of self-reminders. Therefore, the likelihood of using explicit tactics such as self-reminders or inner-speech was not considered to be age-dependent in our experiment. In mixed networks, this intermittent top-down update occurred only after the preparation window was over. During the preparation window, top-down updates to TA units were constant since the only activity at hand was to encode and to retrieve task rules. In between updates, both excited and inhibited TA units decay with the squashing parameter on every cycle. The squashing parameter is the same as the one used for TA units at the end of the trial. This function allows the TA activations to wane without changing the valence of the activation.

Since, in between updates, the TA units do not undergo the activation updates outlined in Equations 2 and 3 of Chapter 5, no input propagated from either the PS-TA fixed connections or from the PS2TA primes, between top-down updates. As with Model 2, the Top signal varied by network age as proxy for developmentally linked constraints on top-down control (Old=10, Middle=6, Young=5).

Unlike in previous models, the TA units were omitted in the pure networks since the tasks could theoretically be carried out without task attribute representations. Instead, the Intrinsic signals were sent to the RO units directly. There was a larger Intrinsic signal towards the 'Yes' response than the 'No' response, with a ratio of 1:0.4. The strength of the Intrinsic signal (interference) to Yes and No was set to 5 and 2, respectively, across all ages.

In Model 3A, all network ages were simulated with increasing update probabilities as a free parameter (0% to 100%). Model 3A involved 25 network subjects in each simulated condition (i.e. update probability level). The number

of trials was the same as in Model 1 and Model 2 (48 trials in the pure condition and 144 trials in the mixed condition).

7.2.2 Model 3A: Result

7.2.2.1 Pure Networks

On pure trials (no TA units), networks at all ages exhibited a reduction in accuracy as well as RT with increasing update probability of the Intrinsic signal (Fig. 7.2). The effect of the Intrinsic signal strength on RT and accuracy was much larger for younger than older networks. In Old and Middle networks, the Intrinsic signal caused problems for accuracy only if the update probability exceeded 50%. In contrast, Young networks exhibited low accuracy at either end of the update probability range—at low probability, Young networks could make time-out errors (response window=600 cycles), while at high update probability, Young networks made errors due to Intrinsic interference.

7.2.2.2 Mixed Networks

Top-down update probability did not modulate RTs in either repetition or switch trials in Middle and Old networks. In contrast, Young networks experienced speed facilitation with a larger top-down update probability in repetition trials, but not in switch trials. It is interesting that this RT facilitation was restricted to repetition trials, as previous models generally showed that switch trials were better facilitated by an additional Top signal than repetition trials. It appears that at very low update probability, the RT on repetition trials in Young networks was comparable to the RT on switch trials. This indicates that Young networks were overall unprepared even on repetition trials. Without further update the TA activations on repetition trials were likely to end up at similar levels as the those in switch trials.

Changes in update probability modulated accuracy on both repetition and switch trials in Middle and Young networks. On repetition trials, Middle networks showed a reduced sensitivity to changes in update probability as compared to Young networks. This is again likely to reflect the quicker response settling and stronger TA update that occurs during the preparation window in Middle networks than Young networks, consequently leaving a smaller number of cycles for the TA activation to decay when the update probability is low. On switch trials, the modulation of accuracy in respect to update probability was similar between Middle and Young networks, but the accuracy was much lower in Young networks than Middle networks across all update probabilities.

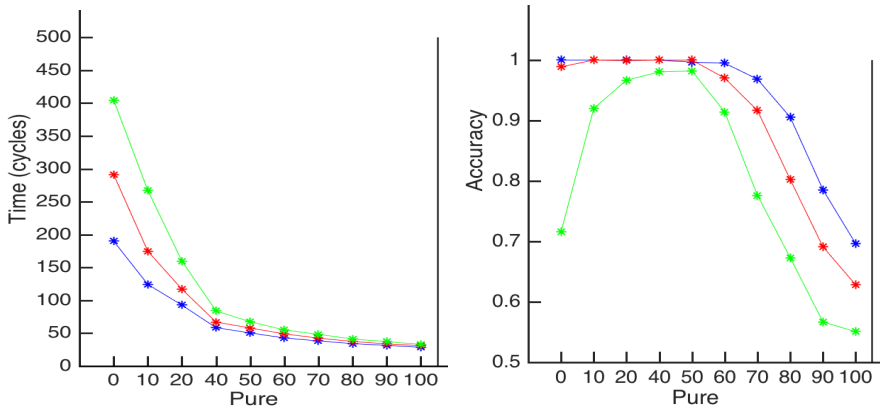

Figure 7.2. Mean RT (cycles) (left panel) and Accuracy (right panel) with increasing update probabilities of Intrinsic signals in pure networks across different network ages (blue-Old; red-Middle; green-Young).

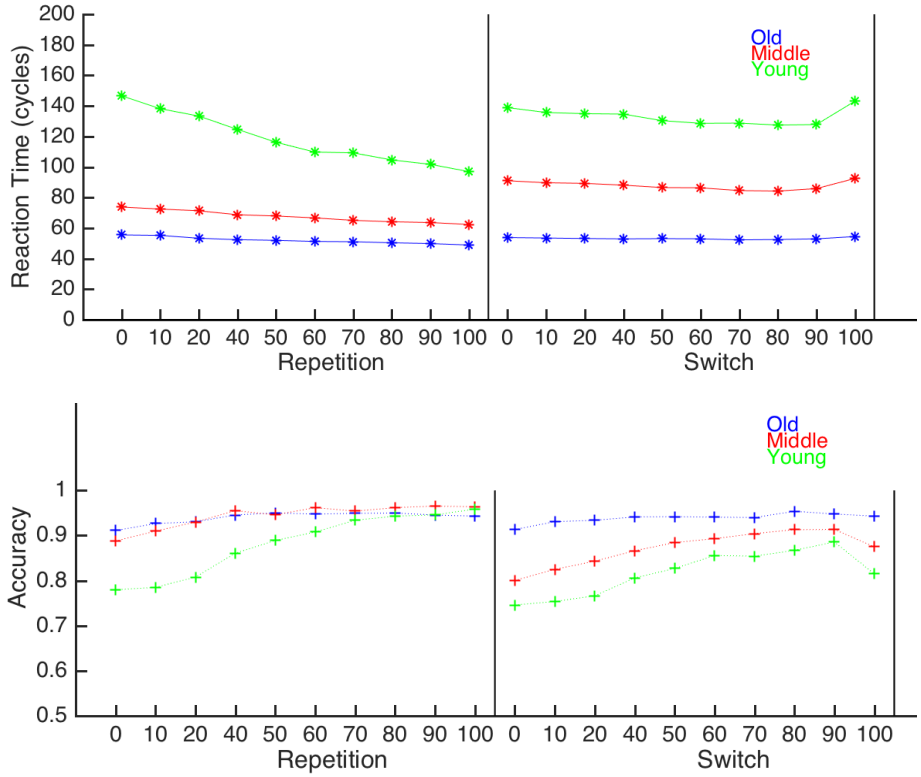

Figure 7.3. Mean RT (cycles) (upper panel) and Accuracy (lower panel) with increasing update probabilities of Top signals in mixed networks across different network ages (blue-Old; red-Middle; green-Young).

Interestingly, there was a reduction in accuracy in Middle and Young networks when the update probability was constant (100%). This may reflect a critical point in the system where the competition between the TA units was relatively strong, despite a relatively high level of TA activation. Further examination (not shown here) revealed that there was an increase in commission errors to the competing response set on switch trials when the update probability was 100%, as compared to when the update probability was 80% (e.g. RO-DY to PS-BV on Bird task). A high update probability not only increases the chance of a successful activation of the task-relevant TA unit on switch trials, but it also increases the chance that the task-irrelevant TA

activation is relatively high at the end of the n-1 repetition trial. As a result, the task-irrelevant TA unit might not be optimally inhibited at the end of the preparation window on a switch trial, leaving room for a possible error and a slowed RT. Thus, the interaction between the update probability and the trial types can result in a critical point where the competition within the system is at the highest.

7.2.3 Model 3A: Discussion

Model 3A consisted of networks with different update probabilities on pure, repetition, and switch trials, at different ages. In the pure networks (without TA), the Intrinsic signal was of a fixed value (Intrinsic signal Yes=5/ No=2) across all network ages. This signal was intended to represent unspecified interference intrinsic to the system. Since pure networks could carry out the tasks perfectly with simple stimulus-response associations, the purpose of the Intrinsic signal is to examine networks' resilience to these spontaneous intrinsic interferences. Although networks at all ages exhibited speed-accuracy trade-offs (i.e. shorter RT and more errors) with increased Intrinsic signal, older networks showed greater overall resilience to interference from the Intrinsic signal. The resilience to intrinsic interference was due to the stronger task-relevant S-R connections in the older network, in relation to the strength of the Intrinsic signal. Only Young networks exhibited errors caused by timeouts. This is in line with the developmental studies which found that children as young as 3 and 4 years often require a substantially larger response window. In fact, even when a sizeable response window is permitted, and even when young children do exhibit the ability to respond within this window, there is still a suspicion that some occasional errors are due to timeout rather than the experimental

variables per se. In many developmental experiments, adopting an exceedingly long response window can be problematic since it can affect the dynamics of the information processes that may otherwise be of interest. Overall, the current model for pure networks offers an explanation as to why young children might exhibit the ability to respond in good time yet display the occasional inability to respond consistently.

In the mixed networks, the update probability refers to the likelihood of self-reminders. Unlike the speed-accuracy trade-offs in the pure networks, the effect of low update probability resulted in performance costs in both RT and accuracy (i.e. longer RT and more errors). There was also a clear effect of network age on the resilience to changes in the update probability, as older networks were more resilient to low update probabilities. This means the range of individual differences on RT and accuracy measures decreased as a function of network age on different trial types—only Young networks exhibited a large range of individual differences in repetition trials (both RT and accuracy); both Young and Middle networks exhibited a sizeable range of individual differences in accuracy in switch trials; Old networks were overall insensitive to changes of update probability.

This indicates that younger children, particularly 4-year-olds, are more likely to exhibit a greater range of individual differences on both RT and accuracy, whereas older children, such as 6-year-olds, were more likely to exhibit the range in accuracy. Adults were not likely to have a greater performance variation on either measure. This observation is consistent with the developmental studies, which often observe large individual differences among young children of a similar age. These variations appear not to reflect developmental constraints, but rather, individual differences. It is possible that

children with different temperaments, motivation, verbal skills or knowledge, may engage with the tasks differently. For example, in tasks that require goal-shifting, despite the fact that all young children have limited capacity to maintain the task attributes, some children may remind themselves of the rules more frequently than others and perform relatively well compared to their peers.

In sum, Model 3A was successful in capturing not only the inter-group differences in accuracy and RT across all trial types, but also the inter-network variations within the same network age. However, beyond the inter-group and inter-individual differences already discussed, Braver (2012) has argued that an additional mechanism operating at the intra-individual level may also be at play. The intra-individual mechanism refers to how the individual approaches the task in a given context. The same person may approach the task proactively or reactively depending on the context. Indeed, it is possible that 4-year-olds, 6-year-olds and adults have completely different interpretations of the task context and consequently different understandings of task demands. For example, adults may understand the task instruction to 'respond as accurately and as quickly as possible' appropriately, and employ their cognitive control accordingly; whereas younger children might not do so. Importantly, differential task strategies may have a direct consequence on the subtler measures reported in the behavioural data, such as the between-condition effects. In Model 3B and Model 3C, I will explore the effect of Intrinsic/Top signal strength and explore different types of task strategies at different network ages, by using a population approach described in the next section.

7.3 Model 3B: Top signal with population approach

As mentioned earlier, individuals across different ages and individuals within the same age may approach the trial types differently, by modulating their Intrinsic/Top signal according to the given context. Although in the pure networks the Intrinsic signal does not correspond to any task strategy, it nevertheless sheds light onto how resilient the system is to levels of interference. In the mixed condition, task strategy may have a direct impact on the observation of between-condition costs. By understanding how Top signal strength modulate task performance, it is possible to speculate about the possible task strategies used at different ages.

7.3.1 Model 3B: Basic assumptions

Model 3B uses a *population approach* to capture the variation in performance on different trial types. According to this approach, a population of networks is constructed by assigning a random update probability to each individual network. This differs from Model 3A where the update probability was the free parameter of interest, and was changed *systematically*, in order to understand its effect on RT and accuracy at different network age. In Model 3B, the update probability is *randomly* generated for each network (e.g. 45% for network subject A, 67% for network subject B and so on for 30 networks at each network age). The between-network differences in update probability correspond to individual differences in how often the participants engage in self-reminding tactics. Since we observed 4-year-olds actively engaging in verbal reminders in the experiments, Model 3B does not make further assumptions on whether children and adults differ in the frequency of verbal updates. The

randomly generated probability setting is used throughout all trials in each simulated network.

The simulations reported here involve 30 network subjects at each age. There were 96 pure trials, and 144 trials in the mixed networks with tasks changed every other trial. As with the previous models and behavioural experiments, targets appeared with 60% probability. There was an increase in the number of network subjects in pure task to minimise the possible effect of outliers since the simulation result was found to be strongly modulated by inter-network differences.

7.3.2 Model 3B: Result

Adopting a population approach with a random probability of Intrinsic/Top signals, Model 3B systematically varied Top signals strengths from 3 to 10 at different network ages (Fig. 7.3).

In the pure networks, older networks appeared to be more resistant overall to the high Intrinsic signal strength than the younger networks. There was a larger decline in accuracy with a larger Intrinsic signal in the younger networks than the older networks. Young networks were consistently lower in accuracy for all levels of Intrinsic signal. However, Old and Middle networks showed relatively similar accuracy. There was a speed-accuracy trade-off (e.g. shorter RT and more errors) on pure trials in relation to the Intrinsic signal. Network age effects on RT became smaller with the increasing Intrinsic signal strength, to the point of no network age differences in RT with a large Intrinsic signal.

Model 3B shows that with probabilistic updates as inter-network differences, accuracies on repetition and switch trials were directly affected by

the strength of top down signals. The modulation of accuracy indicates that the current model is superior to Model 1 and Model 2, where the accuracy variations were largely restricted to switch trials. In mixed tasks, networks at all ages exhibited a very similar pattern in response to changes in the Top signal. They exhibited increased accuracy and shorter RT with a greater Top signal strength. Although there was a very small age effect on accuracy, particularly when the Top signal was smaller (e.g. below 6 on repetition and below 8 on switch trials), the level of Top signal was a more effective predictor of accuracy than network age. In contrast, network age was a better predictor of RT than Top signal strength.

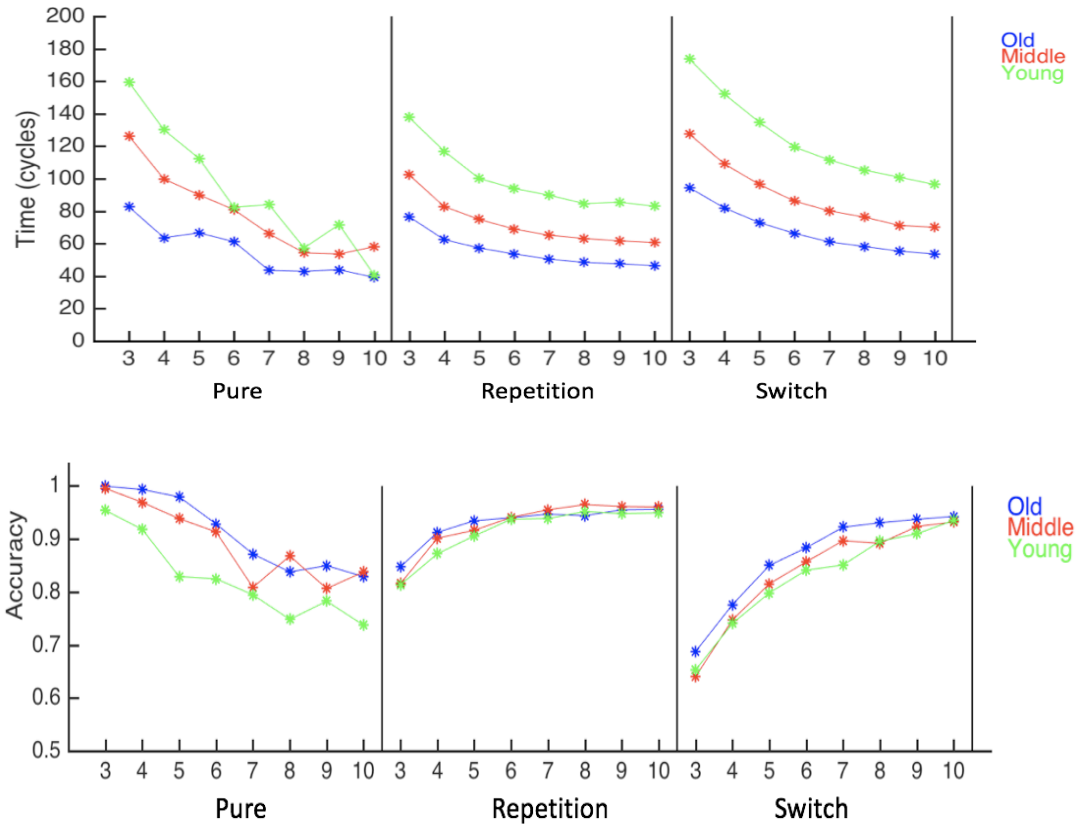

Figure 7.4. The effect Top signals on different trial types. Networks were simulated with population approach (i.e. random update frequency). Top panel shows the effect of Top signal on accuracy; lower panel shows the effect of Top signal on reaction time (cycles). Network ages: blue-Old; red-Middle; green-Young.

To try to understand why the between-condition switch costs did not appear to interact with age in the behavioural experiment is difficult. We can perhaps speculate that children of different ages relied on different task strategies constrained by their level of cognitive development? In the behavioural experiment, the most demanding trials were the switch trials, in which an endogenous effort to retrieve the appropriate task representation is necessary. Thus, a strong Top signal is most likely to happen on switch trials, compared to repetition trials. Although a strong Top signal is assumed more likely on switch trials, the ceiling level of Top signal should still vary by age, as

in the previous models. A younger network should have a lower ceiling level for Top signal, since a high Top signal in younger networks can result in an accuracy level higher than that of an older network (see Model 1B, Chapter 5). This pattern is inconsistent with the behavioural results.

On repetition trials, as no task reconfiguration is necessary, only minimal endogenous effort is needed to maintain, rather than to reconfigure, the task representations. However, how much endogenous effort is employed on repetition trials, in relation to switch trials, may be a matter of task strategy. To understand what task strategies there are in each age group/network ages, Table 7.1 shows the proposed range of Top signal on different trial types at each network age, and their respective accuracies. The accuracies with the specific Top signal in the networks are compared against the accuracies in the behavioural study. Note that each network age has different ceiling Top signals, consistent with the previous models (i.e. Top_{Old}=10, Top_{Middle}=6, Top_{Young}=5).

Table 7.1. Accuracy from the bimodal CMTS study and from simulated result with the respective Top signal

	Behavioural			Model 3B					
				Accuracy			Intrinsic/Top signal		
Age	Pure (%)	Rep. (%)	Swi. (%)	Pure (%)	Rep. (%)	Swi. (%)	Pure	Rep.	Swi.
Adult	98.1 (3.6)	98.3 (3.6)	98.6 (1.7)	98-100	93-96	94	5 to 3	5 to 10	10
6-year-old	94.6 (3.3)	95.9 (4.0)	88.0 (5.7)	94-100	82-94	86	5 to 3	3 to 6	6
4-year-old	84.7 (11.2)	85.9 (8.1)	81.8 (10.3)	83-95	82-92	65-80	5 to 3	3 to 5	3 to 5

Note:

1. The values in the parenthesis are SD. Top signal on switch trial is taken as the developmental constraint (i.e. ceiling level of signal).
2. 2. Age denotes both participant and model age (adult=Old network; 6-year-old=Middle network; 4-year-old=Young network).

7.3.3 Model 3B: Discussion

Model 3B explored the space of possible performance using a population approach by varying update probabilities between networks. Old and Middle networks were reasonably resistant to interference from the Intrinsic signal on pure trials, exhibiting a sharp decline in accuracy only after the signal was greater than 5. Young networks were particularly prone to errors when there was additional intrinsic interference to the response outputs in the system. The differences in the resilience to intrinsic interference has to do with the ratio of the signal between intrinsic interference and the strength of PS-RO connections. A weaker relative PS-RO connection allows a greater opportunity for errors, since the intrinsic interference can overwhelm the evidence from the PS-RO connections. In the mixed networks, all network ages exhibited a similar pattern of response to changes in the Top signal. Network age did not strongly modulate accuracy on repetition trials, and only moderately so on switch trials. In contrast, the network age effect on RT differences was robust across all

levels of Top signal. Therefore, reaction time appears to be firstly dependent on network age (i.e. connection weights) and secondarily on Top signal.

The main significance of Model 3B is that, by modelling networks capable of expressing individual differences, we are able to capture the possible range of accuracies observed within each age group (Table 7.1). Understanding the possible range of accuracies is crucial as it reveals the fundamental age-dependent differences in top-down control and other inter-group and/or inter-individual differences in task strategies. Two questions remain—(i) is a specific age more or less likely to employ a specific task strategy in our experiment?, and (ii) does the between-condition measures depend on the differences in task strategies, development, or both? To address these questions, in the next model (Model 3C), I will explore different approaches to the tasks used in the mixed condition by different age groups. I will also demonstrate how the simulated results can match the behavioural results. Although the performance in the pure condition is not the main focus of Model 3C, since there are no specified task strategies, I will nevertheless still explore whether the simulated results in this condition match the behavioural data.

7.4 Model 3C: Task strategies in different population

7.4.1 Model 3C: Basic assumptions

Model 3C explores what task strategy networks at different ages might employ in the mixed task condition, and what the resulting between-condition costs, as well as inter-group differences would be. As with Model 3A, the ceiling level of Top signal was predetermined by the network age, with a stronger ceiling Top signal used for older networks and a weaker ceiling Top signal used for the younger networks.

However, within the mixed condition task context, different individuals may modulate their cognitive control differently for each trial type. Such modulation is assumed to be closely associated with some form of task strategy, either consciously or unconsciously. Trials may be approached proactively such that a constant high level of control (within what is possible given a specific developmental level of competence) was exercised throughout the series of trials. This proactive control can be taxing, so perhaps not all participants will do so. Alternatively, the participants can approach the tasks reactively, and only exert a greater level of control on the most demanding switch trials, but not on repetition trials. It is also unclear whether children at different ages will approach the tasks differently. For example, it is possible that younger children are more likely to approach the tasks reactively than proactively. It is also possible that the youngest children did not attempt to engage at all, and only employed a bare minimal level of cognitive control necessary for the repetition trials.

As a result, Model 3C employed Top signals specific to a chosen task strategy at each network age—proactive, reactive or no strategy. The main objective of Model 3C was to test which task strategy can produce the best fit to the observed behavioural results. This contrasts with the previous models where the focus was on understanding the effect of parameter settings. In the mixed networks, the tailored Top signals for each trial type and age follows the range in Table 7.1, which were found to capture the accuracies observed in the behavioural experiment. All networks were simulated with both reactive and proactive strategies, but only Young networks were simulated with the minimal 'no strategy' approach (see Table 7.2 for Top signal setting). In the pure

networks, all network ages were simulated with a moderately small Intrinsic signal (signal=5).

Model 3C also adopted a population approach (as in Model 3B); however, instead of choosing a random update probability between 0% and 100% as inter-individual differences, the range is narrowed to 0% and 60%. The reason for this is that the update probability in the mixed condition is conceptualised as the likelihood of giving oneself a verbal task reminder. It seems unlikely that the participants would constantly engage in this practice, and therefore a large update probability may not be appropriate. In the pure condition, when the update probability was very large, as shown in Model 3A, there was a very strong speed-accuracy trade-off that eliminated the age differences in processing speed. Such a scenario was not considered likely in real participants. Therefore, it would appear that whatever the likelihood of interference is in the behavioural studies, it is unlikely to be much larger than the likelihood of processing task-relevant information.

In Model 3C, there were 96 trials in the pure condition and 144 trials in the mixed condition. There were 30 network subjects to each network age

Table 7.2. Top signals by task strategies and Intrinsic signals

	Old		Middle		Young		All
	Rep.	Swi.	Rep.	Swi.	Rep.	Swi.	Pure
Proactive	10	10	6	6	5	5	5
Reactive	5	10	3	6	3	5	5
No strategy	-	-	-	-	3	3	5

Note:

Proactive strategy: large Top signals in all trials in mixed task.

Reactive strategy: a larger Top signal in switch trials than in repetition trials in mixed task.

No strategy: minimal Top signal in all trials in the mixed task.

7.4.2 Model 3C: Result

Figure 7.5 shows the overall performance at each network age by different task strategies.

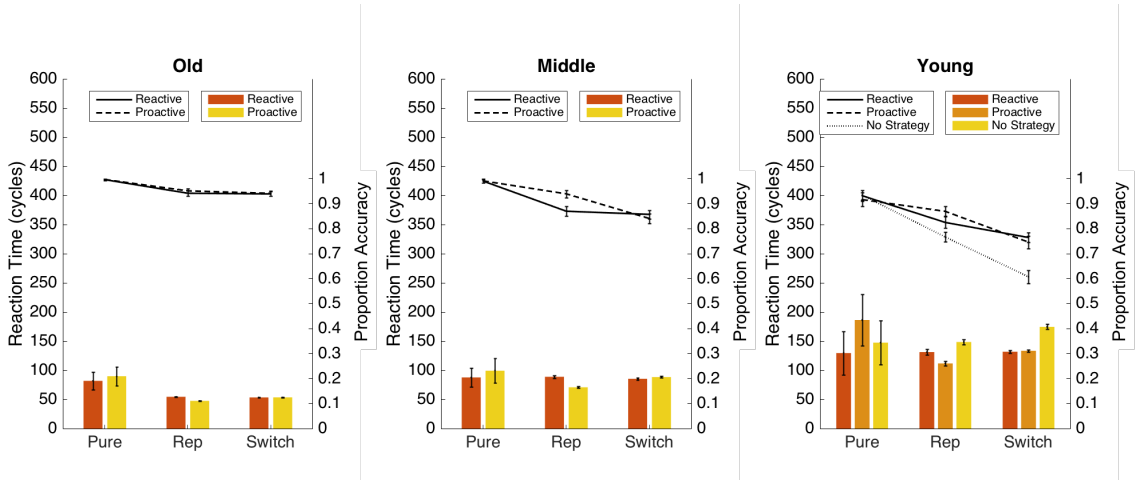

Figure 7.5. Accuracy and reaction time in networks with different task strategies. Left to right: Old, Middle, Young networks. Bars show RT (cycles) and lines show accuracy. Error bars represent 95% CI.

7.4.2.1 Pure trials

In the pure networks, with a moderate Intrinsic signal, the youngest networks exhibited the lowest accuracy and slowest RT. It should be noted that all pure networks within each network age were simulated with the same

Intrinsic signal, so the only difference between the bars of different colours in Figure 7.5 was the population sample, determined by the random update probability. While Old and Middle networks showed relatively stable performance between the population samples, Young networks exhibited a greater range of difference in RT between population samples, and to a lesser extent, of accuracy as well. This highlights the fact that young children with a relatively weak ability to translate mental representations into motor responses exhibit greater effect of individual differences on tasks where a quick stimulus-response mapping is crucial to the chosen measure than in older participants.

7.4.2.2 Mixed trials

The overall accuracy of Old networks in the mixed condition was unaffected by task strategy (Fig. 7.5). However, a proactive approach would result in RT switch costs since the enhanced top-down control facilitated response settling on repetition trials. This interpretation of RT switch costs is somehow different from the traditional view, where RT switch costs were interpreted with a suboptimal control on switch trials as compared to repetition trials (e.g. De Jong, 2000; Rogers & Monsell, 1995; Rubinstein, Meyer, & Evans, 2001). In short, the current model argues that the observation of RT switch costs is related to the task strategy used rather than to cognitive control per se.

The performance of the Middle networks was affected by task-strategy. A reactive strategy did not optimise the accuracy on repetition trials. Thus, within the developmental constraint of possible Top signal strength, to achieve a relatively good performance on repetition trials, a high level of Top signal was needed. In the bimodal CMTS experiment, 6-year-olds exhibited the largest accuracy switch cost. As discussed previously, RT and accuracy switch costs

are most likely with a proactive task strategy than a reactive task strategy, since the performance on repetition trials with a proactive strategy is optimal. The simulation results suggest that at least some 6-year-olds understood the importance of maintaining a good level of task representations through proactive cognitive control. Indeed, anecdotally, many 6-year-olds appeared to exhibit a high level of self-regulatory behaviours during the experiment.

The performance of the Young networks was also affected by task strategy. The accuracy was lowest with no strategy (i.e. minimal Top signal), followed by a reactive strategy and then a proactive strategy. In the behavioural experiment, there was no significant difference in accuracy between repetition trials and switch trials in 4-year-olds, suggesting that most 4-year-olds approached the tasks reactively. In the model adopting a reactive approach would also reduce RT switch costs. This is consistent with the lack of age effect on RT switch costs observed in the behavioural finding.

In the previous behavioural analyses, children who did not pass the 70% accuracy threshold were excluded from the analyses. All these children were 4-year-olds. It is therefore possible that the 4-year-olds with particularly low accuracy may have approached the tasks differently, despite having no difference in the developmental constraints such as processing speed from other 4-year-olds. For whatever reason, these children may not approach the task either reactively or proactively. Instead, they exert little top-down control over the representation of task attributes, and consequently their responses are made primarily by bottom-up stimulus-response associations, reactive PS-TA task activations, and other carry-over effects.

7.4.2.3 Fitting with the behavioural result

Figure 7.6 shows the behavioural results and simulation results with the task strategies that best matches to the behavioural data.

The simulation results allow us to speculate as to the most likely task strategy used by age level. Figure 7.6 (left panel) shows the bimodal CMTS behavioural results with the 70% accuracy exclusion criterion, and the best fitting task strategy by network age (right panel). Old networks were assumed to approach the task conservatively and employ a reactive strategy, Middle networks were assumed to employ a proactive strategy optimised for the different trial types, and Young networks were assumed to employ a reactive strategy. The overall result appears to be a good match to the behavioural data.

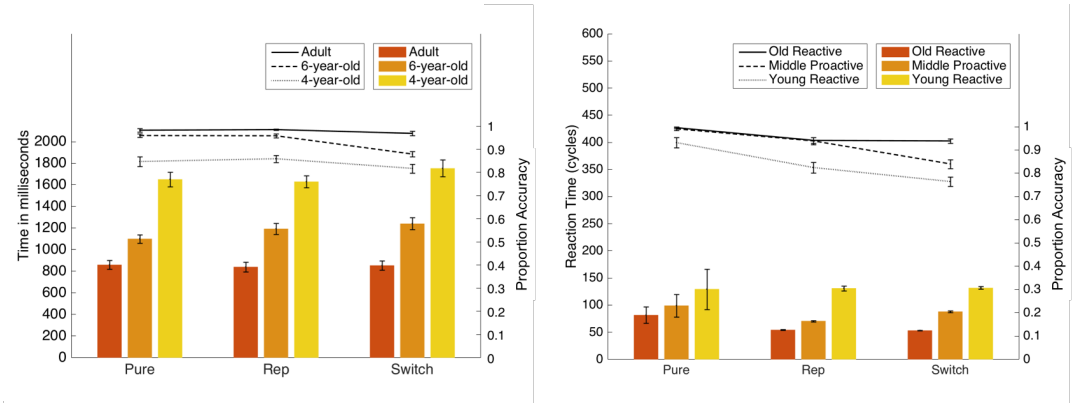

Figure 7.6. Accuracy and reaction time in behavioural experiment (left-panel) and the simulated population models (right-panel). Bars shows RT (ms or cycles) and lines show accuracy. Error bars represent 95% confidence intervals.

Figure 7.7 shows between-condition RT and accuracy costs in the behavioural and the simulated results with models of the best fitting task strategies mentioned previously (Old/reactive; Middle/proactive; Young/reactive). Like with the behavioural results, there was no consistent RT mixing costs when comparing the performance on pure trials with performance on repetition trials. It is likely that mixing costs are not a valid performance measure if tasks can be

structured differently between pure and repetition trials, despite being perceptually similar. It may not always be appropriate to compare performance across these two trial types if the tasks are conceptualised differently by the participants.

RT switch costs are observed only in Middle networks that adopt a proactive task strategy. However, overall, RT switch costs are not modulated by network age, something which is also consistent with the behavioural findings. Although younger children appeared to have a greater RT switch costs in the behavioural result, statistically the differences were not significant. There was also no network age effect on accuracy switch cost, as was also observed in the behavioural results. It is thus possible that the inconsistency in the between-condition costs reported across the published developmental research is largely due to a combination of different developmental cognitive constraints and different task strategies that the children engage to complete a task.

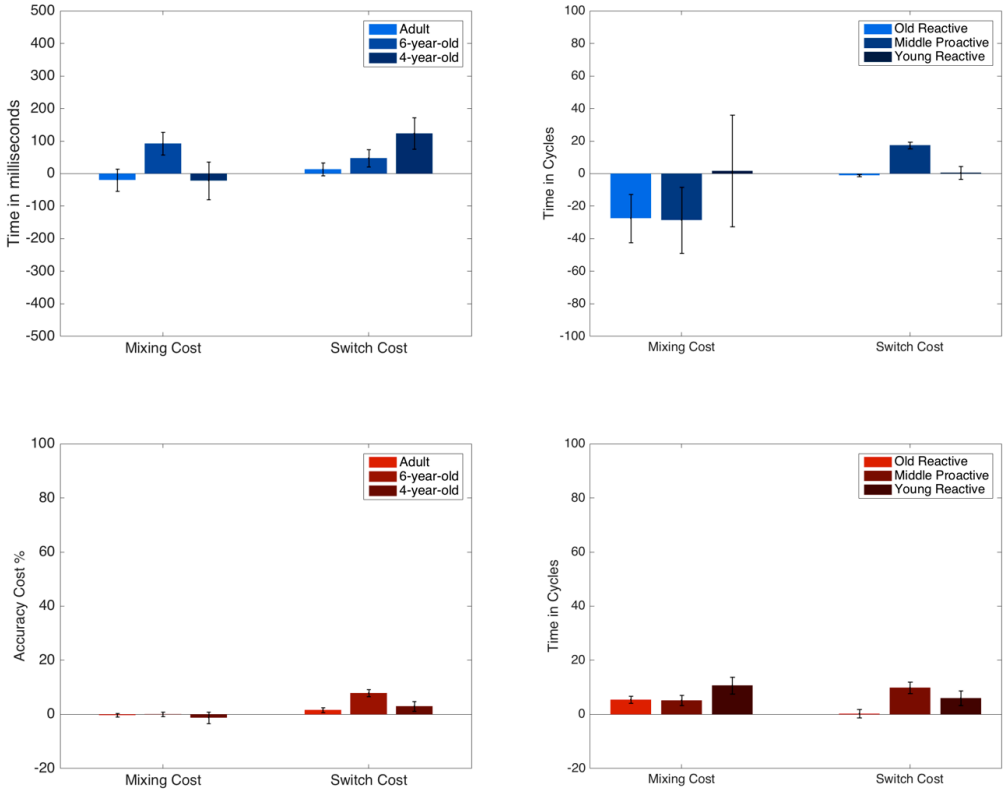

Figure 7.7 Between-condition RT (upper panel in blue) and Accuracy (lower panel in red) mixing costs and switch costs in different ages. Left panels show the behavioural data from the experiment; right panels show the simulated result. Error bars represent 95% CI of means.

7.4.3 Model 3C: Discussion

Overall, Model 3C was the most successful model at capturing the developmental differences in task performance on each trial type, as well as giving an account of how between-condition effects are related to task strategies. Model 3C made a few critical assumptions about how different network ages may exhibit accuracy variations by strategically varying the degree of Top/Intrinsic signals. The specific parameter settings for each task strategy were based on the simulation results in Model 3B, which systematically explored the space of accuracy in relation to changes in the Intrinsic/Top

signals. One could argue that Model 3C over fitted the behavioural data since the simulations were carried out after the parameter search (e.g. the Top signals in Model 3C were chosen from the range that would result in accuracy closely matched to that observed in bimodal CMTS). However, the aim of the Model 3C simulation exercise was to illustrate that the observed behavioural results *can* be produced by the strategic modulation of Top input. Something that was indeed accomplished. Importantly, we do not make claims that the participants of a specific age could *only* employ that specific task strategy; instead, Model 3C merely proposed that the participants of a specific age were more likely to employ a particular task strategy under our experimental design. It is therefore possible that in a different context, the same participant could potentially employ a different task strategy.

It appears that there is no linear relation between task strategy and network age, since both Old networks and Young networks conceptually approached the tasks 'reactively'. It is possible that adults are just as likely to employ a reactive strategy as young children, but for different reasons. Adults are likely to approach tasks adaptively but conservatively, exerting only a necessary amount of top-down control. In our experiments, tasks were relatively easy and therefore adults were able to approach the tasks reactively. In comparison, 4-year-olds might approach the tasks reactively because of developmental constraints on their core cognitive abilities. Although the switch signal (i.e. cue) on switch trials may promote a little boost in top-down control in 4-year-olds, they nonetheless failed to consistently monitor their performance on repetition trials and exert an optimal level of top-down control. Six-year-olds were likely to approach the task proactively, since they were highly accurate but were still below ceiling accuracy, on repetition trials. Anecdotally, most 6-year-

olds did appear to concentrate on the tasks during the experiment. Thus, proactivity and reactivity of task strategies may not serve as direct evidence of the overall cognitive control, particularly when the perceived task difficulty differs between groups.

Model 3C shows that, to really understand what is going on underneath the inter-group and between-condition effects, it is important to understand where the inter-group, inter-individual and intra-individual differences lie, as well as the dynamics of the underlying information processes. The update probability was found to be the parameter most likely to drive inter-individual differences in Young networks but not Old networks. Moreover, the relative modulations in Top signal strength between trial types, conceptualized as task strategy, is crucial in accounting for between-condition differences. Although between-condition effects may not be the most reliable measure for developmental effect, particularly in young children, if additional specifications such as task strategy are given, they may be a useful predictor for developmental and/or inter-individual difference.

7.5 General Discussion

Although deterministic models such as Model 1 (Chapter 5) and Model 2 (Chapter 6) were able to capture the developmental differences in RT, and in accuracy on switch trials, without a dynamic mechanism through which the task-representations are allowed to decay, these models were not able to capture the error profiles on baseline trials (i.e. pure and repetition trials). Model 3 introduced the decay function as well as the update probability function, through which populations of networks can be created. In the behavioural experiment, although young children generally performed less well than older children and

adults, there were also large individual differences within the age group. Having a population model is an effective way of capturing these individual differences. Indeed, the population approach of modelling was able to capture different developmental trajectories of typical and atypical children (Thomas, Davis, Karmiloff-Smith, Knowland, & Charman, 2016; Thomas, Knowland, & Karmiloff-Smith, 2011). In Model 3, the population variation was loosely modelled as the probabilities of task updates, without a specific supposition of how different network ages varied in their update probabilities. The probabilistic task update enabled inter-network differences to emerge in each network ages, and therefore were more effective in capturing the overall performance variations within the network age.

The main objective of Model 3 was to investigate how performance variations are manifested at inter-group and inter-individual levels. Inter-individual differences were modelled with update probability, which is loosely associated with internally generated self-reminders of the task rules. It was found that even if there were large individual differences in update probability at each network age, only younger networks would exhibit a large inter-network variation in accuracy. The upper limit of Top constraint was considered as the inter-group difference by age. Top signal has a direct and strong effect on accuracy in mixed tasks, and a moderate effect on the response time. In our behavioural study, there was a significant age effect on the overall accuracy, and the developmental differences in top-down control may be directly associated with the observed difference. Since Top signal also affected response speed, this implies that within a specific age range, response time may be a valid predictor of the individual differences in top-down control.

However, within developmentally appropriate limits, top-down control can also vary with task strategy. A simple way of defining task strategy is by how much top-down control varies by task context. A task can be approached proactively by consistently employing a good level of top-down control throughout the duration of the overall task. In this case, the level of control may not vary much on a trial-to-trial basis. This task strategy, however, is very effortful and taxing of attentional resource. It is possible that when the tasks are perceived as easy, a savvier participant may approach the tasks reactively. Indeed, the reactive strategy matched our behavioural experiment well in adults since they showed only a very small switch cost. It should be noted that the explanation proposed here for switch costs is quite different from the traditional view of switch cost, in which a large RT switch cost is often seen to reflect suboptimal cognitive control on switch trials. Here, I argue that the small RT switch costs are likely to be caused by a *lower*, not greater, cognitive control on repetition trials, compared to switch trials. This scenario is perhaps most probable if the accuracy on these tasks is at ceiling level, which is often the case with adult task-switching studies, and the participants have greater freedom to approach the tasks with minimally required (and minimally demanding) levels of cognitive control. That task strategy has a direct impact on how switch costs should be interpreted may have great implications for how cognitive control should be measured with this specific paradigm. However, task difficulty is only one factor that may affect task strategy, other factors such as temperament and motivations can also be at play.

In contrast, young children were unlikely to have perceived the tasks as ‘easy’ since they did not achieve ceiling performance. In my observation, the lack of motivation is also not a plausible explanation for their lower performance

since most if not all children were highly engaged in the tasks. The type of task strategy used by young children is perhaps more likely to reflect both inter-individual developmental factors as well as intra-individual differences, in contrast to just the intra-individual differences in adults. Even with a proactive approach, Middle networks could not achieve ceiling performance on switch trials. If the simulation results stand, then 6-year-olds' performance on switch trials may be a useful indicator of developmental constraint on top-down control.

Four-year-olds exhibited a huge variation in performance, with some children achieving above 90% accuracy and others barely at chance level. The children below 70% accuracy were excluded from the behavioural analyses since it was not clear what the underlying reason of this poor performance was. Our simulation model would suggest that these children simply were not engaging the task by adopting a task-appropriate strategy. Instead, they approached switch trials as they would approach repetition trials, with minimal top-down control. In comparison, other 4-year-olds who achieve a good level of overall accuracy may be more likely to adopt task strategies by modulating their top-down control. Specifically, those who achieved a higher accuracy on repetition trials may have some understanding of proactivity. These children are also more likely to exhibit a larger switch cost in both RT and accuracy. In contrast, young children who did not achieve a good level of accuracy on repetition trials were more likely to adopt a reactive task strategy, and counterintuitively exhibited a small RT and accuracy switch cost.

Model 3 demonstrates that pure and mixed tasks can require significantly different information processes. Specifically, representation of the pure task does not require a higher level representation of task attributes. If this is true, then between-condition costs may not be a valid measure of cognitive control

and information interference—particularly if different ages approach the pure task differently. The results in Model 3A suggest that the pattern of speed-accuracy trade-off may be one way in differentiating whether the task is approached with a higher-level goal representation that includes task attributes or not.

In sum, Model 3 highlights the importance of understanding performance variations in relation to factors that affect different levels of comparisons—at inter-group level, inter-individual level, and intra-individual level, and of course, as well as the information processes specific to each task.

Models 1, 2 and 3 have progressively captured greater nuances in the non-linear interactions among information processes, development and inter/intra individual characteristics—Model 1 captured the ideal behaviours with a generalisable task-switching paradigm; Model 2 captured context-specific processes that were potentially significant to young participants; Model 3 captured the individual characteristics within each age group. In the next chapter, instead of task-associated measures, I will explore how modality shift effects could be captured by the model.

Table 7.3 Parameter setting in Model 3

Parameter Name	Old (Default)	Middle	Young
Weights (Pure networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
Lateral connections from RO_{YES} to RO_{NO}	-1.3	-	-
Lateral connections from RO_{NO} to RO_{YES}	-1.0	-	-
Weights (Mixed networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
TA unit to RO_{YES} unit	2.8	2.4	2.0
TA unit to RO_{NO} unit	1.8	1.4	1.0
PS unit to TA unit	3	-	-
Within-set lateral connection from RO_{YES} to RO_{NO}	-1.3	-	-
Within-set connection from RO_{NO} to RO_{YES}	-1.0	-	-
Between-set lateral connections between RO_{Dog} and RO_{Bird}	-1.3	-	-
Inputs (Pure networks without TA unit)			
Intrinsic signal to RO_{YES}*	3 to 10[1]	-	-
Intrinsic signal to RO_{NO}*	1.2 to 4[1]	-	-
PS units (clamped activation)	1	-	-
Bias	-2.5	-	-
Inputs (Mixed networks)			
Top signal	5/10[1,2]	6/6[1,2]	3/5[1,2]
PS units (clamped activation)	1	-	-
Bias	-2.5	-	-
Time constraints			
Preparation window	150	-	-
Timeout	600	-	-
Other parameters			
Priming rate between PS and TA	1	-	-
Priming rate between TA and RO	2	-	-
Step size	0.0015	-	-
Noise	0.006	-	-
Response threshold	0.2	-	-
Min. and max. activation of TA and RO units	-1.0 to 1.0	-	-
Squashing/Decay parameter for TA unit	0.7	-	-
Top-down/ Intrinsic signal update probability*	0 to 100%[1]	-	-

1. For the actual setting in each model, refer to the main text.

2. Default min/max signal on repetition/switch trials

* Indicates new parameter in the current chapter.

'-' indicates the same/similar setting as in Old networks

Chapter 8. Computational model of the modality shift Effect (Model 4)

In Chapters 5 to 7, the models have focused on the possible information processes involved in either pure or mixed task performance. Little attention was paid to the processes involved in shifting attention between modalities. In the bimodal CMTS experiment (Chapter 3), we found a reliable modality shift effect across all ages, and an asymmetry in the modality shift effect (Fig. 8.1). Specifically, the MSE in the pure blocks was nonparadoxical, indicating a larger cost to the harder auditory targets than an easier visual targets. In contrast, the MSE in the mixed blocks was paradoxical, with a larger cost to the easier visual targets than to the auditory targets.

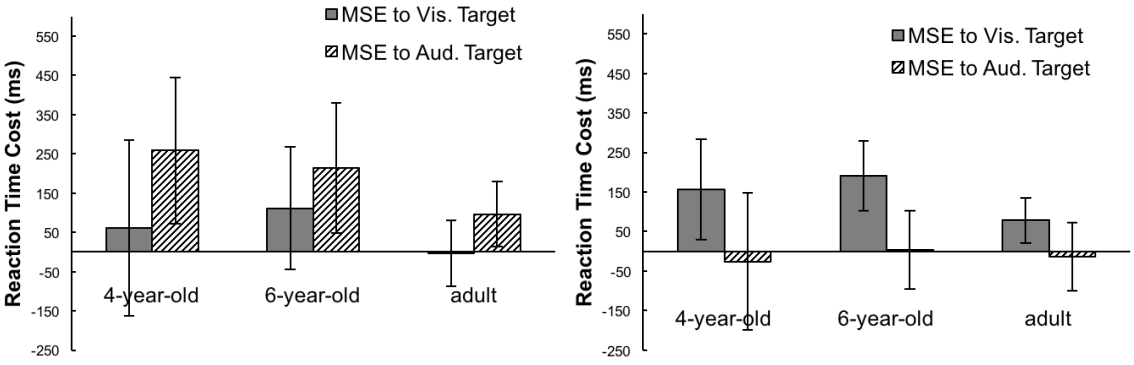

Figure 8.1. Behavioural Result from existing analyses: Modality shift effect in Pure trials (left panel) and Repetition trials (right panel) in the bimodal CMTS experiment. Filled bars show the RT differences (ms) between A2V and V2V trials (MSE to visual target), and hatched bars show the RT differences (ms) between V2A and A2A trials (MSE to auditory target). Error bars represent 95% CI of means (the figures were from original analyses in bimodal CMTS, Chapter 3).

To understand how robust this paradoxical MSE in the mixed blocks was, data from *unimodal CMTS* were re-visited to confirm this paradoxical MSE. Although our computational models did not specifically model unimodal CMTS, the results from this study further confirmed our observations. In the unimodal CMTS, the stimulus was either visual- or auditory-only, and the experiment involved only mixed blocks. The overall performance by target modality in unimodal CMTS was similar to bimodal CMTS experiment (relevant to the current models). That is, in both experiments, the participants were quicker and more accurate in responding to visual targets than to auditory targets, and both experiments found paradoxical asymmetry in MSE in mixed blocks, as the MSE was larger to the easy visual detection, than the harder auditory detection (Fig. 8.1, right panel for bimodal CMTS; Fig. 8.2 for unimodal CMTS). In sum, it appears likely that the paradoxical MSE in the mixed task is characteristic of the situation where tasks are intermixed.

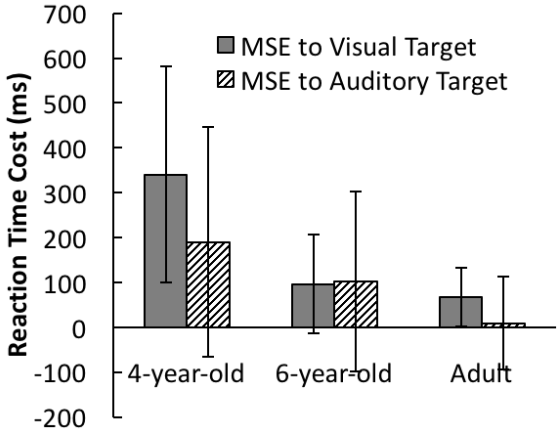

Figure 8.2. Behavioural Result with revisited data: Modality shift effect in Repetition trials in the unimodal CMTS experiment. Error bars represent 95% CI of means (the figure was from a revisited data analysis).

Research on the cross-modal attentional shift effect has often asked whether MSE is part of the task-set shift, mediated by task-associated cognitive processes, or, whether MSE comes from modality-specific processes (Arnell & Jenkins, 2004; Driver & Spence, 2000; Spence, Nicholls, & Driver, 2001). Although the previous models did not consider additional modality-specific representations, they did include priming mechanisms that may result in a modality shift effect. It is possible that the RT was quicker on modality-repetition trials, compared to modality-shift trials, due to stimulus primes. If this is the case, then the priming mechanism might not only be category-specific (i.e. the stimuli from the same target category), but also modality-specific (i.e. within modality). According to the priming account of MSE, the asymmetry of MSE is due to asymmetric modality-response compatibilities—at least in the pure task. In our models, there were stronger connections from the visual PS units to the RO units, than from the auditory PS units to the RO units. These asymmetric pathways were intended to reflect the quicker translation of responses from the visual inputs than from the auditory inputs, as seen in the behavioural results. If this priming account is supported, it would suggest that MSE is not distinct from task-associated effects such as carry-over primes, and that modality information was incorporated as part of the overall task set.

Alternatively, MSE might reflect processes related to additional parallel modality-specific processes. For example, lingering representations about information specific to the modality, termed modality attribute (*MA*), are carried over to the next trial and exert influence on how the subsequent stimulus is processed. In this regard, the residual activation in the MA representations is conceptually similar to the residual activation of the TA representations. The difference between MA and TA representations is the level of information

processing— TA representations are directly mediated by top-down control—thus task-associated, whereas MA representations are likely to be triggered by perceptual inputs per se—thus relatively task-free.

In this chapter, Model 4 explores both the priming account of MSE (Model 4A), and modality-specific representation account of MSE (Model 4B). I will also explore how MSE asymmetry and the reversal of MSE asymmetry might be produced within these accounts.

8.1 Basic assumptions

In this chapter, a model with modality attribute units (Model 4B) will be compared against the model without modality attribute units (Model 4A).

Cost asymmetry is not something unique to MSE. When two tasks differ in difficulty, asymmetry effects have often been reported in unimodal task-switching studies (e.g. Allport, Styles, & Hsieh, 1994; Bobb & Wodniecka, 2013; Ellefson, Shapiro, & Chater, 2006), although the direction of the asymmetry is not always consistent. Gilbert and Shallice's (2002) model successfully captured the asymmetric RT switch costs in these studies. These authors also investigated how different types of asymmetry may occur. In their model, paradoxical asymmetry refers to the larger switch cost to the stronger task (greater connection weights) than to the weaker task. This asymmetry could be induced when the Top signal differed greatly in strength for different tasks. In contrast, nonparadoxical asymmetry referred to the larger switch cost to the weaker task than to the stronger task. This effect was more likely to occur if there were large differences in connection weights between task pathways.

In our behavioural study, the asymmetry in MSE was nonparadoxical in the pure blocks, since the cost was smaller (and not significantly different from

zero) to the stronger visual pathway, and larger to the weaker auditory pathway. As with the nonparadoxycal costs found in Gilbert and Shallice's model, it is possible that with enough asymmetry between the pathway connection weights, MSE asymmetry may be created. Alternatively, the MSE asymmetry may be caused by additional mediators, such as the representations of modality attributes, that can influence how perceptual stimulus is processed. For example, the attention might be tuned to the perceptual-based (in contrast to task-based) attribute specific to the modality, such as the pitch of the sound, due to the previous exposure to that modality attribute. Thus there may be a cost/benefit on modality-shift and modality-repetition trials due to the lingering activation of the modality attribute representations.

While the MSE in the pure blocks may reflect the asymmetry between the pathways, or linger modality attribute representations, our behavioural experiment showed that the effect was reversed in the repetition trials in mixed blocks. Specifically, MSE could only be observed with visual targets, but the MSE to the auditory targets was eliminated in mixed blocks.

The reversal of the asymmetry in the behavioural experiment is puzzling. One possible explanation is that the participants engaged in verbal self-reminders (Blaye & Chevalier, 2011; Kray et al., 2004), which might have interacted with modality-specific processes. To model this account of the reversal of MSE asymmetry, it is necessary to introduce an additional unit that will interact with modality-specific processes Thus, in Model 4B, a unit that represents phonological engagement of task goal is added on top of the modality attribute units in the mixed networks, in order to model the effect of inner speech on modality-specific processes.

Model 4 differs from the previous task-based models in terms of perceptual stimuli. Unlike our previous models where the stimulus could be both uni-selection and bi-selection, all stimuli in Model 4 are uni-selection stimuli (i.e. only one PS unit is activated). This is because, although in the bimodal CMTS experiment all stimuli were bimodal, the specific activation dynamics in the previous models would define the stimuli as either unimodal- uniselection (one activated PS unit) or bimodal-biselection (two activated PS units). Consequently, there is an imperfect match in stimulus set between the computational model and the behavioural experiment.

This problem can be overcome if all the stimuli in the computational model are uni-selection. Thus, the basic assumption of Model 4 is that if a stimulus contains a target, then attention will quickly be drawn towards that modality, and away from the modality of the neutral distractors. On bi-selection trials, it is less clear (even behaviourally) how attention will be deployed between the visual and auditory modalities, since both elements would signal a response. Consequently, for simplicity, the current model focused on understanding the MSE asymmetry with uni-selection stimuli only.

8.2 Model 4A: Priming account with asymmetric pathways

Model 4A[1] has a similar architecture to that of Model 3C (section 7.4), but with a greater asymmetry between the PS-RO pathways, and with a constant perceptual input to PS units. To create an effect of asymmetric MSE, it is necessary for the PS units to be of continuous value and to have residual

[1] All parameters setting used in the simulations with Model 4A are listed in Table 8.1 at the end of chapter.

memory of the n-1 trial. If the PS units are clamped at 1, then the modality-shift trials will be practically identical to the modality-repetition trials. To avoid this, all PS units are initialised to 0.7 to allow scope for PS activation increases as a result of a constant perceptual input. As the PS activation is reduced, the response threshold was correspondingly increased from 0.2 to 0.3 to extend sampling opportunities in the network. This is because a higher response threshold generally allows the RO units to have a greater opportunity in collecting evidence from the associated processing pathways. If the response threshold is set too low, the network will not have enough opportunities to arrive to the correct answer. Unlike the residual activation at the TA level at the beginning of the trial, there is no residual activation at the PS level. The only memory mechanism is priming, and consequently the asymmetric MSE is dependent on the modulations of the priming connections.

When the PS activation is continuous, it is possible that the stronger pathway may not derive as much priming benefit from the increase in PS activation as the weaker pathway. This is because the response settling will be faster and therefore the PS unit is likely to undergo fewer cycles of perceptual updates. Thus, the overall MSE effect in Model 4A will be dependent on PS2RO and PS2TA primes, modulated by the differential response settling speed in each pathway.

The main objective of Model 4A is to understand whether asymmetric MSE can be created without the addition of modality attribute representations. There were 30 network subject of each network age. As with the previous simulations, only correct Yes responses were analysed. There were four trial types in each condition. These are modality-repetition trials (MR) such as V2V and A2A, and modality-shift trials (MS) such as A2V and V2A, where the first

letter denotes the target modality of the n-1 trial and the second letter denotes the target modality of the current trial. As in the behavioural experiment, only pure trials and repetition trials were of interest. In the behavioural experiment, there were intervening task cues on switch trials so it would not be appropriate to analyse MSE on these trials. To compensate for the fewer data points for each trial type (MR_{Pure}, MS_{Pure}, MR_{Rep}, MS_{Rep}) compared to task-associated trials, we increased the number of total trials from our previous models. In Model 4A, there were 160 pure trials and 120 repetition trials.

8.2.1 Model 4A: Result

8.2.1.1 RT and Accuracy.

The results show that overall the networks were more accurate in Model 4A than in Model 3C (Fig. 8.3), and this is possibly due to relatively slow response settling in Model 4A as a consequence of the smaller initial PS activations and the raised response threshold. A slower system could result in an increase in accuracy since RO units had a greater time window for collecting evidence from the information pathways.

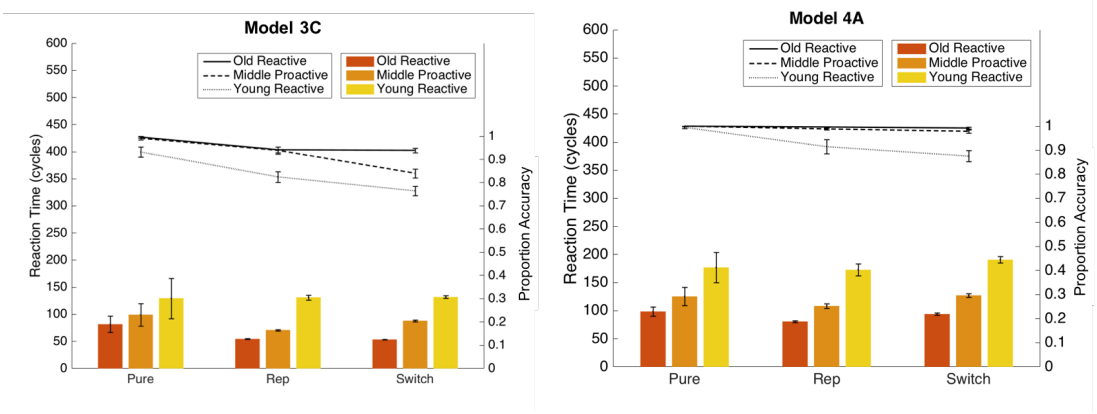

Figure 8.3. Accuracy and reaction time in Model 3C (left-panel) and Model 4A (right-panel). Bars represent reaction time (in cycles) and lines represent accuracy. Error bars represent 95% CI of means.

8.2.1.2 Modality Shift Effect

Visual processing was much faster than auditory processing in Model 4A (Fig. 8.4). This was expected since the PS_{Vis}-RO pathway was much stronger than the PS_{Aud}-RO pathway. The modality shift effects (MSE) to either visual or auditory targets are shown in Figure 8.5. With the asymmetric pathway strengths, there was a larger MSE to the auditory target than the visual target in both pure and repetition trials. This is because the PS activations in visual trials were smaller than in auditory trials, since response settling to visual targets was fast, and therefore PS_{Vis} was not updated as strongly as auditory targets. The weaker PS_{Vis} activation means that the priming facilitation on the next trial would be relatively smaller than the stronger PS_{Aud} activation. On repetition trials, as there was no additional mechanism in place to modulate the MSE effect, no reversal of asymmetry was observed, despite some reduction in the overall priming effect.

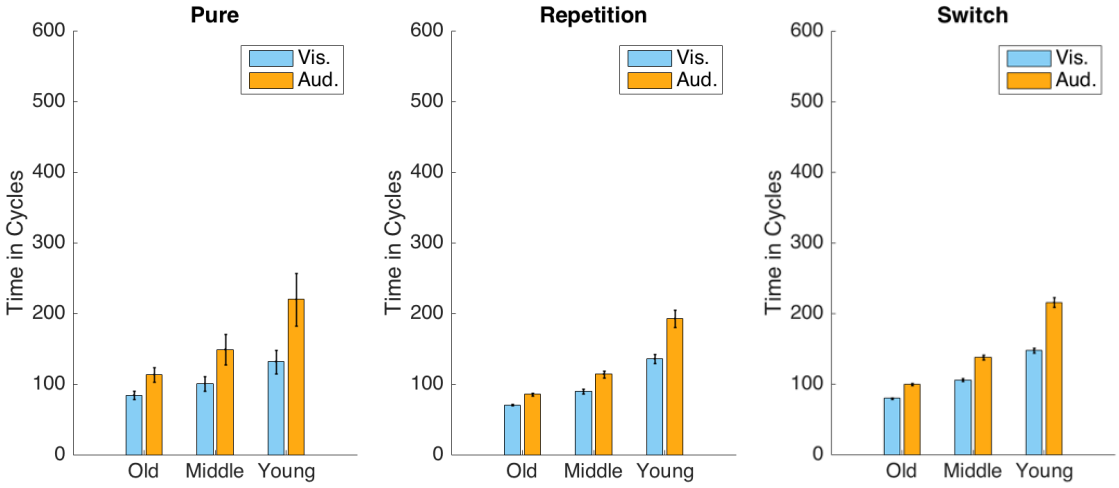

Figure 8.4. Model 4A: Reaction time in cycles to visual targets (blue bars) and auditory targets (orange bars) on different trial types and network ages. Left to right panels: Pure, Repetition and Switch trials. Error bars represent 95% CI of means.

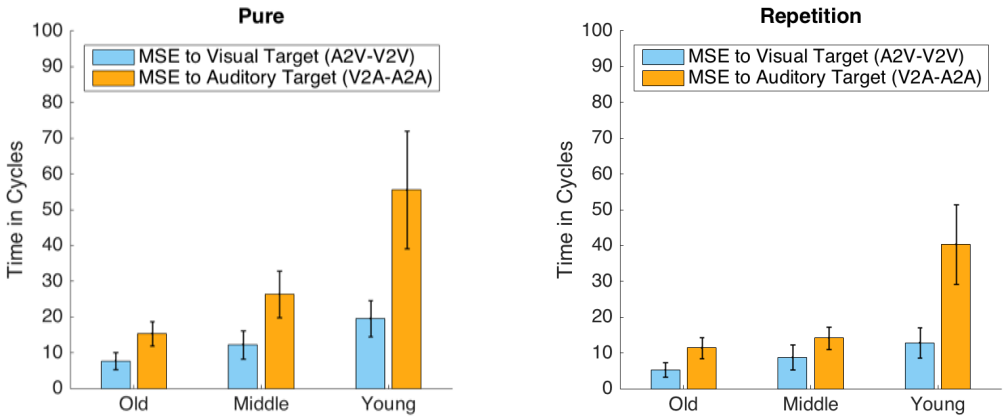

Figure 8.5. Model 4A: Modality shift effect in Pure trials (left panel) and Repetition trials (right panel). Blue bars show the RT differences (cycles) between A2V and V2V (MSE to visual target), and orange bars show the RT differences (cycles) between V2A and A2A (MSE to auditory target). Error bars represent 95% CI of means.

8.2.2 Model 4A: Discussion

Model 4A demonstrated an asymmetric cost since the MSE cost was larger for the weaker auditory pathway than the stronger visual pathway. In Gilbert and Shallice's model, the nonparadoxical asymmetric switch cost was caused by the interplay among the asymmetric pathway strengths, the residual activation of the TA units and the relatively similar Top signals across two tasks. Unlike in their model, Model 4A lacked residual activation since PS units were initiated anew on each trial. Instead, differences between modality-shift and modality-repetition trials were created through the priming connections. In Model 4A, the asymmetric MSE was due to the differences in priming strengths arising from the interplay between the asymmetric pathway strengths and the PS activation at the end of the trial. On visual trials where the pathway strength was stronger, the PS unit was updated for a limited number of cycles, since the network settled into a response relatively quickly; in contrast, on auditory trials, the PS unit was updated for a greater number of cycles and thus the PS activation was greater at the end of the trial. The differential activation of the PS units resulted in the differential priming facilitation on different trial types (visual vs. auditory trials). It is therefore plausible that the asymmetric MSE effect on pure trials in the behavioural experiment reflects a priming effect and thus was not different mechanistically from the other task-associated effects discussed in the previous models.

Although Model 4A was able to capture the asymmetric MSE pattern on pure trials, there were still disparities between the behavioural results and the simulated results. In the behavioural results, not only was the MSE to visual and auditory nonparadoxically asymmetric in the pure blocks, but only the MSE to the auditory target was reliably different from zero. The reverse was true on the

repetition trials in the mixed blocks, where paradoxical asymmetry was observed, but only the MSE to visual targets was reliably different from zero. With priming connections, the facilitative effect on modality-repetition trials is likely to be deterministic. Thus it is unlikely that a mean MSE of zero or a reversal of asymmetry could be achieved within the priming account.

An explanation of the asymmetric MSE based on this priming account relied on a few awkward assumptions. For example, in the pure condition, to create a mean MSE to visual targets around zero, it would be necessary to eliminate or reduce the priming effect on visual trials. This can be achieved by a mechanism that reduces the PS_{Vis} activation during the settling process; but even so, any PS_{Vis} activation at the end of the trial is likely to result in priming facilitation on MR trials in pure networks. Even more challenging would be to reverse the nonparadoxical asymmetry to paradoxical asymmetry, while reducing the MSE to auditory targets towards zero. It is not clear how this can be achieved with only a priming account of MSE.

In sum, although asymmetry can be observed with Model 4A, the specific patterns of the MSE in the behavioural experiment make it unlikely that MSE was wholly due to an asymmetric priming effect. Although priming effects may be at play, since the stimuli on MR trials were also from the same stimulus category as the previous trial, it cannot account for the overall pattern observed in the experiment. Therefore, Model 4B investigates whether MSE can be achieved without resorting to a priming account, by removing all priming connections and by adding mechanisms that can modulate PS activation with residual activations from previous trials.

8.3 Model 4B: Modality attribute representations

Model 4A showed that with just the asymmetry in connection weights, without an additional modality-based mechanism that modulates PS activations, the resulting asymmetry pattern was not wholly satisfactory. One way to modulate PS activation is through attentional biases from the modality attribute representations. The rationale here is that when a bimodal stimulus contains a target, after sufficient encoding of the stimulus, attention is quickly tuned to the modality that contains the target, and away from the modality that contains a distractor. It should be noted that this is different from simple activation of perceptual-based modality processing, since the representation of modality attribute is essentially 'selected' based on stimulus saliency. The definition of 'modality attribute' here does not refer to a specific representation. Rather, it may encompass all representations that relate to the information presented in that modality. This 'attribute' may be the visual-spatial/ auditory-spatial aspect of the input, as well as features within the stimuli (e.g. greyscale images on the screen/ volumes, pitches and temporal dynamics coming from the headphone).

In addition to understanding the nonparadoxical asymmetry through modality attribute representations, an additional mechanism is needed to account for the paradoxical asymmetry in MSE in the mixed blocks. Although it is currently not clear what mechanisms underlie the change in direction of the MSE asymmetry, one mechanism stood out to be most probable—namely verbal self-reminders. In Model 3 (Chapter 7), we have already introduced the idea of an intermittent Top signal as a form of self-reminders. This self-reminder may be presented in the form of verbal rehearsal in 4-year-olds, and inner speech in 6-year-olds and adults. This phonological or verbal representation of the task goal is likely to interact with modality-specific processes. To model the

interaction between verbal representation and modality attribute representation, an additional Phonological Engagement unit is introduced in the mixed networks only, which will interact with modality attribute units.

Model 4B[1] reverted back to using the same weight setting as in Model 3C since the default weight setting was already shown to be appropriate to for a range of different simulations. In contrast to Model 4A, there were no priming connections between either PS and RO or between PS and TA in Model 4B. This is because Model 4B specifically set out to test whether MSE reflects other independent processes distinct from the previous task-associated processes, including the priming effects.

The overall architecture of Model 4B is shown in Figure 8.6. The additional units and connections in the network are discussed in the following section.

[1] All parameters setting used in the simulations with Model 4A are listed in Table 8.2 at the end of chapter.

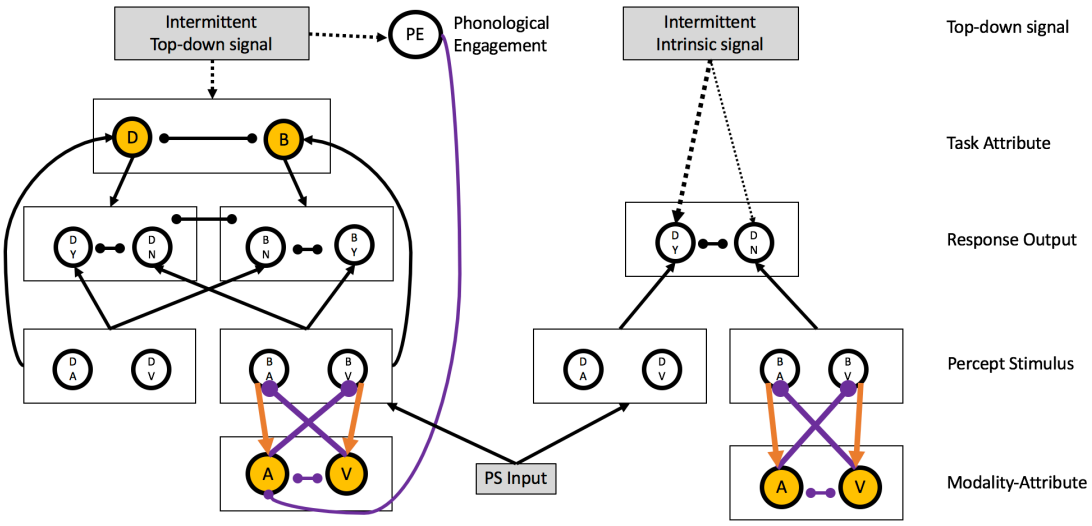

Figure 8.6. Model 4B architecture in the pure (right network) and mixed networks (left network). Coloured connections are additional fixed connections—purple inhibitory connections and orange excitatory connections. PE: phonological engagement unit. Filled units are allowed to have activations carried across the sequence of trials.

8.3.1 Model 4B: Model architecture

Modality attribute layer *(MA)* has two units—an auditory MA unit, and a visual MA unit. The MA units are connected to the PS units, with an excitatory connection from the PS units to the corresponding MA units (e.g. DV and BV to MA_{VIS}), and an inhibition connection from the MA unit to the competing PS unit (e.g. MA_{VIS} to DA and BA). The inhibition connections from the MA units to the cross-modal PS units mean that PS activation is modulated by the competing modality, not the associated modality.

At the theoretical level, having excitatory PS-MA and inhibitory MA-PS connections emphasises that the differential attentional bias towards the PS units is dependent on cross-modal modulations. We believe that the selection between audio and visual inputs in an audiovisual stimulus is more likely to

interact with cross-modal representations rather than within-modal representations. This assumption is based on the many studies with multisensory information that have documented cross-modal effects when the stimuli were bimodal, in which the information of one modality could either facilitate or interfere the information associated to the other modality, compared to baseline unimodal stimuli (Colavita, 1974; Nava & Pavani, 2013; Robinson & Sloutsky, 2004; Sinnett et al., 2008). To model this cross-modal influence, it is more appropriate to have cross-modal interactions between MA and PS layers. As mentioned previously, we do not know what this modality attribute would correspond to in real life, but it might be helpful to make an explicit speculation for illustrative purpose. For example, if this modality attribute representation in the MA_{AUD} unit is the pitch of the auditory input, on A2V trial where MA_{AUD} unit carried lingering activation from the n-1 auditory trial, the active memory of this 'pitch' information would weaken (i.e. inhibit) the representation of the visual input at the PS level.

There is also a practical reason for having cross-modal, rather than within-modal, interaction between MA and PS. If the connections between MA and PS were bidirectional and excitatory, it creates a feedback loop with a relatively strong effect from the current stimulus (since the MA to PS feedback input would be directly influenced by the current PS unit). This would not be appropriate since the modality shift effect is dependent on the modality attended to on the previous trial. In comparison, with the inhibitory connections from the MA to the cross-modal PS units, the effect from the n-1 MA activation can be more keenly felt since on modality-shift trials, the current PS unit does not strongly influence the residual cross-modal MA activation from the previous trial (although there are still lateral connections through which interactions do occur).

The weights of the excitatory connections from PS to MA are the same across all network ages. This is because the PS to MA connections were assumed to reflect an automatic pop-out effect of the PS units from the target set. Once the perceptual-stimulus representation is sufficiently activated, it is assumed that this automatic activation of modality attribute representation is the same across all ages. In contrast, the inhibitory connections from MA to PS units were different in different network ages—older networks had stronger inhibitory feedforward connections than younger networks. This is because these inhibitory connections were designed to reflect cross-modal selective attention with bimodal input, which is assumed to be slower in young children than adults.

As with other processing units, there are lateral inhibitory connections between visual and auditory MA units, as well as a bias to the net input. Both pure networks and mixed networks have these additional MA units.

PS units in Model 4B take on continuous activation values, in contrast to the clamped activation of 1 in all previous models (other than Model 4A). The PS units are updated with the input from the MA units through the inhibition connections that link them. The net effect is a reduction of PS activation if the cross-modal MA unit was positive, or an increase in PS activation if the cross-modal MA unit was negative. For example, if the MA_{AUD} is positive, which is likely to be caused by the residual activation from the n-1 trial, and the current stimulus is DV (Dog-Visual), then the DV PS unit is expected to decrease in activation to such a point that the MA_{VIS} is sufficiently positive (positive inputs from DV to MA_{VIS}) to inhibit the MA_{AUD} through lateral inhibition.

In addition to the input from the MA units, the PS units also receive a constant perceptual input since (in the experiment) the stimulus was always

present throughout the trial. As a result, there is a natural tendency to maintain or to update PS activation, unless the cross-modal MA unit is highly positive. Unlike TA units where the activations linger between sequences of trials, PS unit activations are initiated anew at the beginning of every trial. The visual and auditory PS units are initialised to a different value, with a maximum activation for the visual PS units (activation=1), since it was assumed that visual information was immediate and complete at the stimulus onset. In contrast, the auditory PS units were initialised to a lower value at 0.8 since it was assumed that the identification of an auditory input requires a greater level of temporal integration than a visual input. The minimum and maximum activations of the PS units are set between 0 and 1. The same PS setting and update functions were applied to both pure and mixed networks.

The *phonological engagement* (PE) unit is an additional unit in the mixed networks only. The role of this unit is to represent an engagement of the verbal rehearsal, which is assumed to interact with the MA units. The unit is either *on* '1' or *off* '0', depending on whether there is a top-down update, and irrespective of the magnitude of the Top signal. This unit is not modelled in the pure networks since the network architecture does not involve task representations. It is not immediately clear how the PE unit might interact with the MA units; however, the behavioural data may provide some clues here.

An elimination of MSE to auditory targets in the mixed blocks may reflect either that (a) there was an additional facilitative effect to the auditory processing that overshadowed the benefit of a modality-repetition, or (b) there was an additional interfering effect to the auditory processing that overshadowed the cost of a modality-shift. In the case of a facilitative effect to auditory targets in the mixed blocks, we may expect the RT difference between

visual target detection and auditory target detection to narrow from the pure to the mixed blocks (e.g. RT to visual and auditory targets become more comparable). There was no such trend in the behavioural data (Fig. 8.7). In fact, the difference in RT between visual and auditory target detection became much larger in the mixed blocks than in the pure blocks.

In the second case, the verbal self-reminders may interfere with auditory processing. Since phonological representation and auditory processing are likely to tap into a common attentional resource, verbal self-reminders may eliminate the benefit of modality-repetition. Thus, in accordance with this hypothesis, I implemented a negative input from the PE unit to the MA_{Aud} unit such that whenever the PE unit is activated it sends an inhibitory input to the MA_{Aud} unit.

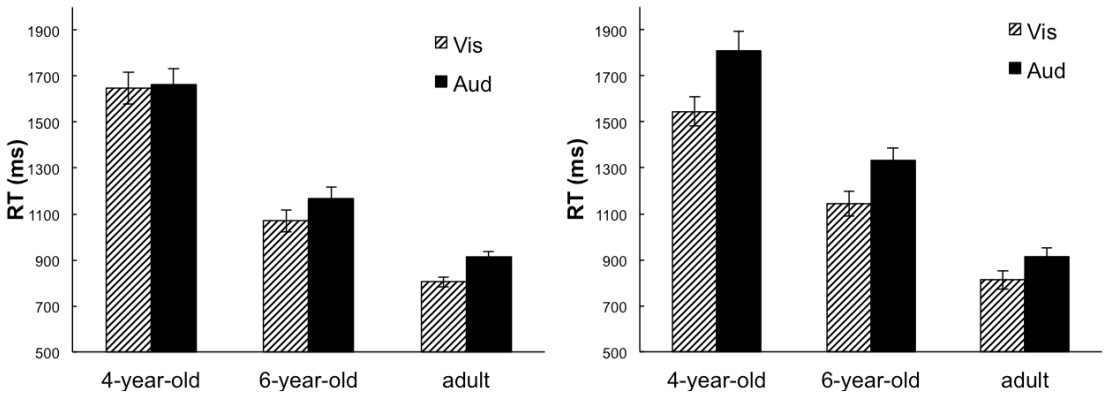

Figure 8.7. Behavioural Result: Mean reaction time (ms) to different visual or auditory targets in different age groups. Left panel: pure blocks; right panel: mixed blocks. Error bar represents 95% CI.

MA Squash is the squashing parameter for the MA units at the end of the trial. As with the TA units, a proportion of the activation of the MA units was carried on to the next trial. The MA squash parameter determines how much residual activation was allowed to remain from trial to trial.

In addition to the MA Squash parameter, on nontarget trials, the model made no assumption of which MA unit should be activated. In the model, the MA activations were set to 0 at the end of the trial if no target was present. Resetting the MA units at the end of the nonresponse trials prevented the MA activation from growing too strongly over successive nonresponse trials. In the behavioural experiment, a correct 'Yes' response was taken as evidence that the participant had attended to a specific modality, but there was no assumption regarding which modality the participant was attending to on nonresponse trials. The same rationale was therefore applied to the current model.

8.3.2 Model 4B: Network Operations

Figure 8.8 illustrates the schematic flow of the network operation.

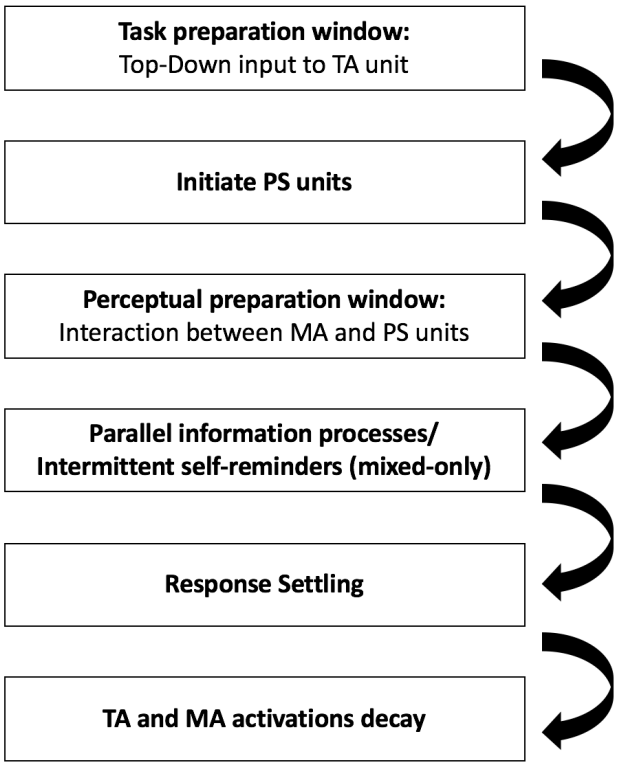

Figure 8.8. Schematic illustration of stages of network operations in Model 4B.

As with the previous models, the simulation started with a preparation period with a constant Top input to the TA units. However, in addition to the task preparation window, after the stimulus onset, there was an additional preparation window for perceptual processing. Unlike the goal activation process where the TA units were gradually updated from low initial activation values, the PS activations were initialiseded with fixed values at stimulus onset.

Once the PS activations were initialised, MA representations started to interact with the PS units. Specifically, it is assumed that the influence from the n-1 modality attribute activation happens at the early stage of perceptual processing. The main purpose of the *perceptual preparation window* was to

allow the residual MA activation to modulate PS activations before the response settling process started. The duration of the perceptual preparation window is critical as to whether the PS activations are influenced by the residual MA activations or by the MA activations of the current PS (through lateral inhibition). If the perceptual preparation window is too small, the PS units might not be updated enough to reflect the status of the n-1 MA activations; conversely, if the perceptual preparation window is too long, the PS units might reflect the current target modality more than the n-1 target modality.

The PS units were subject to the influence of the MA units for a number of cycles before the response settling commenced. During the perceptual preparation window, activations propagations were allowed only between the PS units and the MA units, as well as from the constant perceptual input to the PS units.

Once both task and perceptual preparation windows were over, the network started settling towards a response. The perceptual input was constant throughout the trial, since the percept stimulus was always present in the behavioural experiment. The interactions between MA and PS units were also constant across the trial. As with Model 3C, the Top signal was probabilistic with inter-network differences (e.g. network subject 1 updates TA frequently, whereas network subject 2 only updates occasionally). In the mixed network, when the Top signal was present, it simultaneously turned on the phonological engagement unit (PE) to capture the assumption that top-down updates were dependent on the verbal rehearsal of the current task attribute. The PE unit was either on '1' or off '0' and it had a small inhibitory connection to the MA_{AUD} unit (as mentioned previously). As in Model 4A, the response threshold was increased from 0.2 to 0.3 to reflect the smaller PS inputs.

There were 30 network subjects to each network age, with 160 pure trials, 120 repetition trials, and 120 switch trials. As with the previous models and behavioural experiments, targets appeared with 60% probability. The number of network subjects and the number of trials were increased in Model 4B because of the limited number of data for each trial type.

8.3.3 Model 4B: Result

The developmental differences in RT observed across all trial types were preserved in Model 4B (Fig. 8.9). Moreover, as with Model 4A, young networks exhibited higher accuracy overall than Model 3C. The reason behind the higher accuracy might be the same as in Model 4A in which the larger response threshold might have created greater opportunities to arrive at the correct response. Finally, achieving high accuracy rates also allowed the current model to generate a greater number of data points for the analysis of modality shift effects (MSE).

The MSE in Model 4B and the MSE in the bimodal CMTS study are shown in Figure 8.10 and Figure 8.1 at the beginning of the chapter. The MSE in pure networks and in mixed networks will be discussed separately.

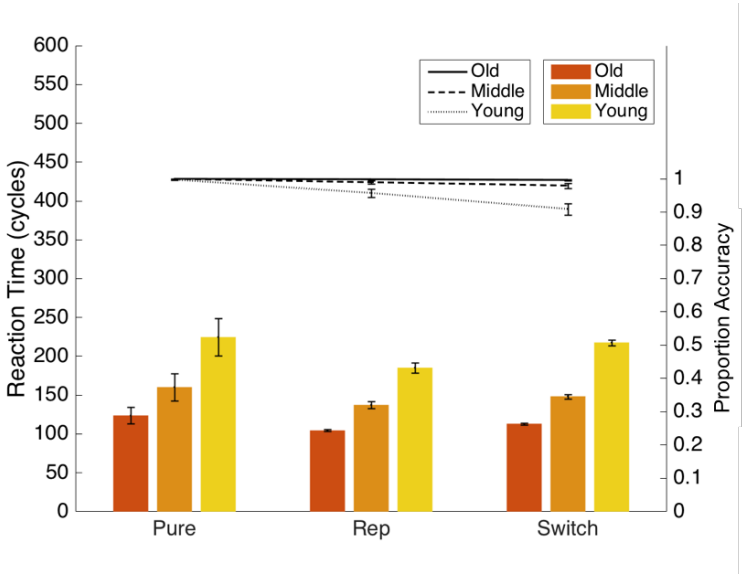

Figure 8.9. Accuracy and reaction time in Model 4B. Bars represent reaction time (in cycles) and lines represent accuracy. Error bars represent 95% CI of means.

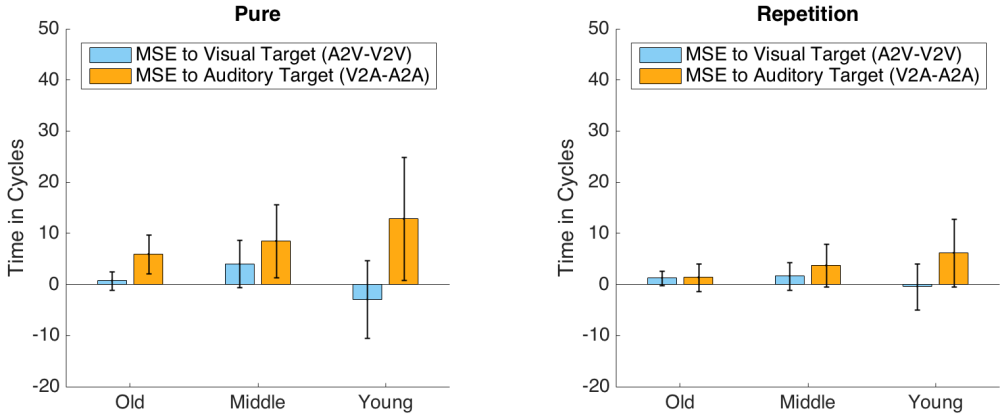

Figure 8.10. Modality shift effect in Pure trials (left panel) and Repetition trials (right panel). Blue bars show the RT differences (cycles) between A2V and V2V (MSE to visual target), and yellow bars show the RT differences (cycles) between V2A and A2A (MSE to auditory target). Error bars represent 95% CI of means.

8.3.3.1 Pure trials

The MSE in the pure networks exhibited an asymmetric shift cost (Fig. 8.10, left panel). Like in the behavioural experiment (Fig. 8.1), there was a larger MSE to the auditory target (V2A-A2A) than to the visual target (A2V-V2V). More importantly, MSE was only reliable to auditory targets, but not to visual targets. The overall result appears to have a better fit to the behavioural data than Model 4A, in which, despite achieving asymmetric MSE, the networks also exhibited a large MSE on trials with visual targets.

Since the model did not have other n-1 influences such as priming on response settling, the asymmetric MSE in pure networks was caused by the different dynamics in PS activation updates on modality-repetition (MR) and modality-shift (MS) trials. The PS_{AUD} unit was initiated at 0.8, below the maximum of 1, to allow for upward or downward updates. The MSE on auditory trials reflects the differences in the activation gain/loss between A2A and V2A trials. On A2A trials, the inhibited MA_{VIS} unit increased the activation of the PS_{AUD} unit from the very beginning of the perceptual preparation window. In contrast, on V2A trials, the cross-modal MA_{VIS} was activated at the early stage of the processes, thus it was likely to result in a loss of PS_{AUD} activation through the inhibitory pathway. This loss is stopped only when the MA_{AUD} is sufficiently activated, due to the constant perceptual input, which in turn inhibits the MA_{VIS} unit.

The MSE on visual trials was absent because there was no further scope for activation gains for PS_{VIS} unit on V2V trials, since the PS_{VIS} unit was initialised at the maximum value. Although there were no activation gains on V2V trials, similar to V2A trials, there was an activation loss on A2V trials during the early stage of processes. It would appear that this early activation loss has a

limited effect on the overall response settling on A2V trials, since there was no significant MSE to visual targets on pure trials.

In sum, the MSE effects in the pure networks suggest that these effects may largely be attributable to activation gains on MR (modality-repetition) trials, rather than activation loss on MS (modality-shift) trials, during the course of response settling.

8.3.3.2 Repetition trials

On repetition trials, it was expected that the MSE to auditory targets would be reduced by moderating the PS_{AUD} activation on both A2A and V2A trials through the intermittent inhibitory inputs from the PE unit. This is because on A2A trials, the mild inhibitory input from the PE unit can lessen the level of inhibition on the MA_{VIS} unit (the source of MR facilitation to auditory targets), through reducing the positive net input into the MA_{AUD} unit. The negative input from the PE unit, in its functional term, has a similar effect as the bias to the MA_{AUD} unit, since both factors determined how much net input is needed to positively update the activation of the MA_{AUD} unit. The end result is that MA_{AUD} is more likely to be only mildly excited on trials with an auditory target, regardless of the status of the modality transition (repetition or shift). As the MA_{AUD} is only mildly excited, this essentially means that MA_{VIS} is also likely to be only mildly inhibited (the source of positive inputs to PS_{AUD} unit). The overall result is a limited activation gain on the A2A trials in the mixed networks, as compared to the larger gain on the A2A trials in the pure networks.

On V2A trials, the residual positive activation of the MA_{VIS} unit will reduce the PS_{AUD} activation from the initial activation (PS_{AUD}=0.8) at the beginning of the trial. However, this reduction is quickly stopped after the MA_{AUD} becomes

sufficiently positive (through PS_{AUD} input), and the MA_{VIS} unit was inhibited (through lateral inhibition connections and bias). Like for the A2A trial, due to the negative input from the PE unit, at the end of the response settling process, both MA units were likely to be only mildly excited and mildly inhibited.

Thus, the critical difference between the MSE to auditory targets in the pure and in the repetition trials is how progressively inhibited the cross-modal MA_{VIS} unit was throughout the trial. This, in turn, determined how much the PS_{AUD} unit gained in activation. The cross-modal MA_{VIS} was overall more inhibited in the pure networks, than in the mixed networks, and thus PS_{AUD} units in pure networks were more likely to exhibit larger activation gains.

Although the MSE to auditory targets appeared not to be significantly different from zero, thus replicating the behavioural result, there was no reversal of the asymmetry (Fig. 8.10, right panel). Since the MSE in Model 4B mainly reflects information gain on the MR trials rather than information loss on the MS trials, PS_{VIS} unit initialised at the maximum value did not benefit from modality repetition.

8.3.4 Model 4B: Discussion

Model 4B was successful in capturing the asymmetric MSE cost on pure trials. In particular, the MSE to auditory targets was reliably larger than zero, but the MSE to visual target was not reliably different from zero. The reason for the asymmetric cost was due to the differences in the scope allowed for PS activation gain. When the stimulus was visual, the PS activation was already near maximum at the beginning of the trial. On an A2V trial, even if there was an inhibitory input from the auditory MA unit due to the residual activation, the loss of PS_{VIS} activation was not significant enough to alter the

course of response settling. In comparison, on V2V trial, even if there was an excitatory input from the auditory MA unit due to the unit being inhibited on the n-1 trial, since the visual PS unit was already at ceiling activation, there was little scope for upward updates.

When the stimulus was auditory, the PS activation was high but there was still scope for further upward or downward updates. On an V2A pure trial, there was likely to be inhibition from the visual MA unit due to n-1 residual activation. However, with the constant perceptual input, the auditory PS activation was likely to be maintained. In comparison, on an A2A pure trial, there was likely to be positive input from the inhibited visual MA unit, in addition to the constant perceptual input. Thus, the activation of the auditory MA unit on A2A trial was likely to be greater than that on the V2A trial in the pure condition, resulting in an overall faster RT.

On repetition trials, there was a partial success in capturing the MSE to auditory targets, but not to the visual targets—success as in the MSE to auditory targets was not reliably different from zero in any network age, since the error bar crossed the zero point. The small inhibitory input from the PE unit appeared to push the the PS_{Aud} activation to be closer to the initial activation values on either MR or MS trials. On an A2A trial, the positive input from the cross-modal inhibited MA_{Vis} unit was likely to be downregulated due to the lateral inhibitory interaction (i.e. positive input into the MA_{Vis} unit) with the mildly inhibited MA_{Aud} unit—mildly inhibited because of the occasional gating function (i.e. negative input) from the PE unit. On a V2A trial, PS_{Aud} is likely to receive negative input from the positive MA_{Vis} unit at stimulus onset, but this effect was likely to be counteracted by the constant perceptual input. Once the response settling started, the auditory MA unit was still unlikely to gain much ground from

the PS_{Aud} unit due to the gating function from the PE unit. The overall effect on V2A trials appears to be relatively moderate. PS_{Aud} activations on both A2A and V2A trials were likely to stay around the initial activation values without ever reaching the maximum.

Although the confidence interval of mean MSE to auditory targets on repetition trials crossed zero, the absolute mean values in Middle and Young networks still appear comparably larger than the behavioural result. However, this is likely to be caused by the suboptimal parameter tuning in those networks.

Nonetheless, Model 4B failed to capture the MSE effect to visual targets on repetition trials. To create such an effect requires a mechanism that facilitates the differentiations between PS_{Vis} activations on V2V and A2V trials. Since PS_{Vis} was initiated at the maximal value at the beginning of the trial, it would be necessary to update the activation downward on modality-shift trials, and this could only happen if the cross-modal auditory MA unit was high at the beginning of the trial (thus inhibiting the PS_{Vis} unit). Unfortunately, the auditory MA unit was unlikely to gain much activation due to the small inhibition from the PE unit in the mixed condition.

Finally, the dynamic interactions among all the processing layers in the mixed networks in Model 4B make it challenging to predict how the model would behave with a specific parameter change or a combination of parameter changes. There was also the possibility that the mechanism that increase MSE effect to visual targets on repetition trials was different from the mechanism that eliminates the MSE effect to auditory targets on repetition trials.

8.4 General Discussion

Model 4 investigated possible mechanisms that could account for the asymmetry of MSE costs observed on pure and repetition trials, with either a task-focused architecture, or a task-and-modality parallel processing architecture. Both task-focused (Model 4A) and task-and-modality networks (Model 4B) were able to create asymmetry MSE at the population level. However, only Model 4B was also able to capture the statistical equivalence of the behavioural result in terms of whether the MSE was reliably different from zero cost or not. The model suggests that phonological engagement activities (such as verbal self-reminders) interacted with cross-modal selective attention, and that it is the interaction of these processes that causes the MSE to auditory targets on repetition trials. However, none of the models could explain the reversal of asymmetry from nonparadoxical on pure trials, to paradoxical on repetition trials.

The increase in the MSE to visual targets in the mixed blocks (vs. pure blocks), may be due to processes independent to the modality attribute representations. Model 4B incorporated multiple modality-specific factors such as the asymmetry in stimulus-response compatibility (i.e. asymmetry in PS-RO pathways), differences in temporal integration of semantic information (i.e. different initial PS activations), cross-modal selective attention (MA-PS inhibitory connections), and the additional inhibitory effect to MA_{AUD} from the probabilistic verbal rehearsal. Yet our model was not able to capture the large MSE to visual targets in the mixed blocks. It is possible that other information processes not explored in our model are needed to account for the large MSE to visual targets.

Our model shows that asymmetry can happen for many different reasons. These different types of asymmetry can create complex inter-trial effects. At this point in time, our simulation results suggest that modality-based measures such as the size and the direction of MSE can change as functions of pathway asymmetry, initial activation of the perceptual representation, additional modality attribute representation and additional cognitive process. Thus MSE reflects composite effects of multiple information processes. Our previous models (Chapter 5 to 7) focused on task-associated effects, and were successful at capturing developmental differences in RT and accuracy on each trial type. These differences are likely to be dependent on baseline response speeds arising from factors such as connection weights and Top signals. Although between-condition effects such as mixing costs and switch costs were not always good indicators of cognitive control, particularly when the accuracy on baseline trials (e.g. pure and repetition trials) differs between age groups, our models show that all things being equal (i.e. accuracy, as was the case in Models 1 and 2), even between-condition measures may exhibit reliable developmental differences in control mechanisms.

Cross-modal effects, on the other hand, were likely to arise from the lower-levels of processing. Although verbal self-reminders may interact with modality-specific processes, these processes may not implicate higher level cognitive operations. Thus, switching between tasks and shifting between modalities are likely to engage different parallel information processes. Modality shift costs, therefore, do not appear to be good indices of the development of cognitive control per se.

In the next chapter, I will provide an overall discussion of the results of the behavioural studies and how our computational models can account for the

observed behaviours. I will also talk about other mechanisms that might be at play, but that have not been investigated in our models. Additionally, I will highlight the limitation of our models. Finally, I will make a few predictions for future research.

Table 8.1 Parameter setting in Model 4A (Priming Model without MA units)

Parameter Name	Old (Default)	Middle	Young
Weights (Pure networks)			
PS_{VIS} unit to RO unit	4.7	3.7	3.3
PS_{AUD} unit to RO unit	3.6	2.6	2.2
Lateral connections from RO_{YES} to RO_{NO}	-2.0	-	-
Lateral connections from RO_{NO} to RO_{YES}	-1.0	-	-
Weights (Mixed networks)			
PS_{VIS} unit to RO unit	3.9	3.5	3.1
PS_{AUD} unit to RO unit	2.8	2.4	2.0
TA unit to RO_{YES} unit	2.8	2.4	2.0
TA unit to RO_{NO} unit	1.8	1.4	1.0
PS unit to TA unit	3	-	-
Within-set lateral connection from RO_{YES} to RO_{NO}	-2.0	-	-
Within-set connection from RO_{NO} to RO_{YES}	-1.0	-	-
Between-set lateral connections between RO_{Dog} and RO_{Bird}	-2.0	-	-
Inputs (Pure networks without TA unit)			
Intrinsic signal to RO_{YES}	5	-	-
Intrinsic signal to RO_{NO}	2.0	-	-
PS_{VIS} initial activation*	0.7	-	-
PS_{AUD} initial activation*	0.7	-	-
PS input*	3.5	-	-
Bias	-2.0	-	-
Inputs (Mixed networks)			
Top signal on switch trial	8	6	4
Top signal on repetition trial	8	6	4
PS_{VIS} initial activation*	0.7	-	-
PS_{AUD} initial activation*	0.7	-	-
PS input*	3.5	-	-
Bias	-2.0	-	-
Time constraints			
Task preparation window	150	-	-
Timeout	600	-	-
Other parameters			
Priming rate between PS and TA	2	-	-
Priming rate between TA and RO	2	-	-
Step size	0.0015	-	-
Noise	0.006	-	-
Response threshold	0.3	-	-
Min. and max. activation of TA and RO units	-1.0 to 1.0	-	-
Min. and max. activation of PS unit*	0 to 1.0		
Squashing parameter for TA unit	0.7	-	-
Top-down/ Intrinsic signal update probability	0 to 100%	-	-

* Indicates new parameter in the current chapter.

Table 8.2 Parameter setting in Model 4B (with MA units)

Parameter Name	Old (Default)	Middle	Young
Weights (Pure networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
PS units to MA units*	3	-	-
MA units to PS units*	-15	-10	-7
Lateral connections from RO_{YES} to RO_{NO}	-2.0	-	-
Lateral connections from RO_{NO} to RO_{YES}	-1.0	-	-
Lateral connections between MA_{VIS} and MA_{AUD}*	-2.0	-	-
Weights (Mixed networks)			
PS_{VIS} unit to RO unit	3.0	2.6	2.2
PS_{AUD} unit to RO unit	2.8	2.4	2.0
TA unit to RO_{YES} unit	2.8	2.4	2.0
TA unit to RO_{NO} unit	1.8	1.4	1.0
PS units to MA units*	3	-	-
MA units to PS units*	-15	-10	-7
PS unit to TA unit	3	-	-
Within-set lateral connection from RO_{YES} to RO_{NO}	-2.0	-	-
Within-set connection from RO_{NO} to RO_{YES}	-1.0	-	-
Between-set lateral connections between RO_{Dog} and RO_{Bird}	-2.0	-	-
Lateral connections between MA_{VIS} and MA_{AUD}*	-2.0	-	-
Inputs (Pure networks without TA unit)			
Intrinsic signal to RO_{YES}	5	-	-
Intrinsic signal to RO_{NO}	2.0	-	-
PS_{VIS} initial activation*	1.0	-	-
PS_{AUD} initial activation*	0.8	-	-
PS input*	3.5	-	-
Bias	-2.0	-	-
Inputs (Mixed networks)			
Top signal on switch trial	8	6	4
Top signal on repetition trial	8	6	4
PS_{VIS} initial activation*	1.0	-	-
PS_{AUD} initial activation*	0.8	-	-
PS input*	1.5	-	-
Bias	-2.0	-	-
Input from PE unit to MA_{AUD} unit*	-1.0	-	-
Time constraints			
Task preparation window	150	-	-
Perceptual preparation window	30	-	-
Timeout	600	-	-
Other parameters			
Priming rate between PS and TA	0	-	-
Priming rate between TA and RO	0	-	-

Table 8.2 Parameter setting in Model 4B (with MA units)

Parameter Name (cont.)	Old (Default)	Middle	Young
Other parameters			
Step size	0.0015	-	-
Noise	0.006	-	-
Response threshold	0.3	-	-
Min. and max. activation of TA and RO units	-1.0 to 1.0	-	-
Min. and max. activation of PS unit*	0 to 1.0		
Squashing parameter for TA unit	0.7	-	-
Squashing parameter for MA unit*	0.5	-	-
Top-down/ Intrinsic signal update probability	0 to 100%	-	-

* Indicates new parameter in the current chapter.

'-' indicates the same setting as in adult networks

Chapter 9. Discussion and future direction

In this chapter, I will first outline the main empirical results from the behavioural experiments, specifically with respect to task-associated findings and modality-associated findings. This will be followed by a description of the findings from the computational models, which include— (1) the main mechanisms that determine performances, (2) sources of individual differences within each age group, and (3) task structures defined by external instructions and by internal representations (i.e. with or without a goal). I will also outline other potential mechanisms not incorporated in the models, and discuss the limitation of our models. Finally, the chapter will end with some recommendations for future behavioural research.

9.1 Task-associated empirical findings

A series of task-switching studies using stimuli with different modalities and task attributes, requiring either within- and cross-modal attentional shifts, and different with switch predictabilities, showed that children as young as four years old have the requisite ability to switch between competing tasks. Most young children performed well above chance level across these experiments.

The task procedures in the unimodal TS (Chapter 2) and bimodal CMTS (Chapter 3) experiments were similar, involving both a pure-task condition and a mixed-task condition in which the task switched at a fixed interval. Our final unimodal CMTS experiment (Chapter 4) was designed to be the most challenging. This task involved relatively abstract task attributes, random task switches, and no preparation window. The participants of each age group exhibited comparable overall accuracies across the three experiments. With

regards to between-condition effects, we found reliable mixing effects (in both RT and accuracy measures) and switch effects (in RT only) across all ages in the unimodal TS experiment. In the bimodal CMTS experiment we found reliable switch effects (in both RT and accuracy) but no mixing effects (in neither RT nor accuracy) across all ages. Finally, in the unimodal CMTS experiment (involving only the mixed task condition) we found reliable switch effects (in both RT and accuracy) across all ages in. Taken together, repetition trials and switch trials appear overall to be more challenging than their respective baseline trials (i.e. pure trials and repetition trials respectively).

However, having the requisite ability to do something, and having the skill to excel are two different things. While young children exhibited the ability to attend to multiple tasks, and to respond to environmental changes, most 4-year-olds were far from ceiling accuracy on baseline trials (e.g. pure and repetition trials). In comparison, 6-year-olds were only slightly less accurate than adults. Taken together, our behavioural results suggest that for whatever reason, younger children, particularly 4-year-olds, were much more likely to lose control than adults.

Despite these age differences in overall performance, surprisingly, when using conventional between-condition measures such as mixing and switch effects, there were few developmental differences in either measure across all the experiments. If between-condition costs index additional task demands on the more difficult trials (e.g. Altmann & Gray, 2008; Meiran & Kessler, 2008; Reimers & Maylor, 2005; Rogers & Monsell, 1995), we would have expected younger children to have greater difficulty in responding to these additional demands. These suppositions were not supported in our experiments.

Our studies are not the first to report a lack of age effect in between-condition costs. Many other developmental studies also found limited age effects with these conventional between-condition measures (e.g. Davidson, Amso, Anderson, & Diamond, 2006; Dibbets & Jolles, 2006; Ellefson, Shapiro, & Chater, 2006; Reimers & Maylor, 2005). Since each trial type in task-switching studies implicates multiple cognitive operations, it may be hard (with behavioural studies alone) to ascertain the reason for this lack of age interaction with between-condition effects while accounting for the apparent lower overall accuracy in children. To this end, our computational models became instrumental in understanding how between-condition effects can be masked by other factors that determine the overall accuracy in young children.

9.2 Modality-associated empirical findings

Modality associated effects were explored with respect to concurrent cross-modal interactions, namely modality dominance, and inter-trial effects, namely modality shift effects (MSE). The current thesis also explored whether the defining feature of a task set incorporated modality-associated attributes.

Modality dominance was explored in the bimodal CMTS study. Past studies have generally reported visual dominance in adults (for a review, see Spence, Parise, & Chen, 2012) and auditory dominance in young children (Nava & Pavani, 2013; Robinson & Sloutsky, 2004; Sloutsky & Napolitano, 2003). Our experiment found that modality dominance could be measured with RT, rather than just error types; and in tasks with meaningful and familiar stimuli (e.g. animal categories), instead of the usual novel and asemantic stimuli (although see Wille & Ebersbach, 2016, for experiment with semantic stimuli). In our experiment, the modality dominance effect was measured by how much

RT was slowed when the target was presented with a cross-modal distractor, as compared to when the target was presented alone (i.e. unimodal stimulus) in a pure task context. Our results support the idea of a transition from auditory dominance to visual dominance during the course of development, as 4-year-olds experienced greater RT slowing with auditory distractors, and adults experienced greater RT slowing with visual distractors. Both visual and auditory distractors appeared to be equally distracting to 6-year-olds.

Although modality dominance was at play when bimodal stimuli were used, this was only part of the story in an overall task set. All ages were likely to be quicker (in both unimodal and bimodal CMTS) and more accurate (in unimodal CMTS) in responding to visual targets than to auditory targets. This may be due to multiple advantages in visual processing in our experiments. These advantages include the better stimulus-response compatibility between visual-manual than auditory-manual associations (Stephan & Koch, 2010; Stephan, Koch, Hendler, & Huestegge, 2013), and a smaller demand in temporal integration when encoding semantic visual information, as compared to semantic auditory information. Thus, 'auditory dominance' or 'visual dominance' does not necessarily translate to a quicker or a better performance to the dominant modality. The overall performance to a modality-specific target depends on multiple task- and stimulus-dependent factors unique to each experiment.

Modality shift effects were investigated in order to examine more closely the cost in shifting directed attention in both bimodal and unimodal CMTS. Our studies also found asymmetries in the MSE in the bimodal CMTS study. In 6-year-olds and adults, the direction of asymmetry in the pure condition was nonparadoxical, since the MSE was greater to the slower/less accurate auditory

detection than to the faster/ more accurate visual detection. This was not surprising given the multiple advantages in visual processing in the experimental design, in addition to the visual dominance effect (if present, i.e. adults). Thus, responding to visual targets in the pure condition was inherently 'easier' on multiple levels, regardless to the modality transition of the targets. In contrast for 4-year-olds, the direction of asymmetry in the pure condition was paradoxical—a greater MSE to the dominant auditory modality than to the nondominant visual modality. Although 4-year-olds were likely to have an auditory dominance through concurrent cross-modal interactions, they might still experience other task- and stimulus-dependent advantages of visual processing, such as the benefit of visual-manual compatibility and faster temporal integration of semantic visual inputs.

Task-switching studies also often report asymmetric RT switch costs, which happen when the competing tasks differ in the level of difficulty (e.g. Allport, Styles, & Hsieh, 1994; Ellefson et al., 2006; Yeung & Monsell, 2003). The similarities between asymmetric MSE and task-switch costs prompted the question of whether a similar top-down mechanism was also involved in shifting attention between modalities (e.g. Kreutzfeldt et al., 2015). This appears unlikely since, despite one task-switch cost being larger than the other, costs associated with switching to either easy or hard tasks were statistically significant in those studies (e.g. Allport, Styles, & Hsieh, 1994; Ellefson et al., 2006; Yeung & Monsell, 2003). In contrast, the MSE in our study was only found to auditory targets, but not to visual targets in the pure condition in the bimodal CMTS. Our results suggest that MSE may be due to mechanisms not associated with the control required to switch between tasks. The larger MSE to

auditory targets in the pure condition may simply reflect a certain advantage of visual processing in our experimental setting (at least in 6-year-olds and adults).

However, our unexpected finding with 4-year-olds suggests that when modality dominance and task-modality compatibility (e.g. S-R compatibility) differ in their respective directions, one effect may overshadow the other. Similarly, Lukas, Philipp and Koch (2014) also reported a paradoxical MSE—a greater MSE cost to the faster/more accuracy modality than to the slower/less accurate modality; although in their experiment, instead of the usual visual dominance in adults, they found auditory dominance with temporal judgement tasks (i.e. judging the duration of the stimulus). They argued that modality dominance reflects modality-task appropriateness. According to Modality Appropriateness Theory (Lukas et al., 2014; Stephan & Koch, 2010), modality-specific inputs can be more or less effectively processed, depending on how compatible the inputs are with the task dimensions. Thus, MSE might be a composite effect of multiple processes, including concurrent cross-modal interferences, modality-task compatibilities and a shift in directed attention.

If the MSE is indeed a composite effect of multiple processes, it might be less surprising to observe a reversal of cost asymmetry when the task conditions changed. In the mixed blocks in bimodal CMTS as well as in unimodal CMTS (re-analysed data shown in Chapter 9), MSE was greater to the easier visual targets than to the harder auditory targets. Although not explicitly tested, this reversal of the MSE asymmetry may be caused by additional cognitive operations specific to the mixed blocks, compared to the pure blocks—namely verbal self-instruction. Past literature suggests that verbal self-instructions or inner speech are particularly useful tactic for task management (Cowan, Saults, & Morey, 2006; Emerson & Miyake, 2003;

Karbach & Kray, 2009; Kray et al., 2008), thus it is plausible that participants in our studies recruited this task tactic in the more difficult mixed condition. We suspect that this verbal forms of self-reminders may interact with MSE through changing how attention is directed in the experiment, causing a reversal of asymmetry from nonparadoxical to paradoxical. However, this reversal is less likely to happen in the 'modality-based task-switching' studies with task sets defined by modalities, instead of meaningful abstract tasks (e.g. Kreutzfeldt et al., 2015; Lukas, Philipp, & Koch, 2010; Sandhu & Dyson, 2012). In these modality-based 'tasks', the participants were cued to attend to the imperative modality only, but the abstract task goal remains unchanged (e.g. localisation). Therefore, arguably, there was no switch in task goal despite a shift in the attended modalities. This again highlights the lack of consistency and consensus in defining what a task is, and what the requisite cognitive operations are in these tasks. Nonetheless, our results show that MSE are likely to interact with multiple stimulus- and task-level operations, and should be differentiable from task-switch costs.

9.3 Interactions between task and modality

In contrast to the abovementioned modality-based tasks (e.g. Kreutzfeldt et al., 2015; Lukas, Philipp, & Koch, 2010; Sandhu & Dyson, 2012), not explicitly cuing modalities as part of an overall task set allowed us to ask how 'amodal' the task sets were in our studies. Our unimodal CMTS was designed to address this question by looking into how different attentional shift costs added up when both modality and task changed. Hunt and Kingstone (2004) argued that if attentional control in shifting between modalities and switching between tasks depend on shared cognitive resources, RT should be longest

when both dimensions (task and modality) changed, and the costs should be additive; in contrast, if they rely on independent systems, the RT cost on modality-shift task-switch (MSTS) trials should reflect one or the other type of attentional shift cost. Adult cross-modal task-switching studies with supramodal task goals have generally reported mixed results: the additional demand in modality-shift, on top of a task-switch, incurred an RT cost that was less than expected (Hunt & Kingstone, 2004; Sandhu & Dyson, 2013). On another occasion modality-shift could facilitate task-switch (Murray et al., 2009). Thus, past studies have been inconclusive about whether modality-associated processes and task-associated processes are independent or interdependent.

Adding to these mixed findings, our studies did not find a less-than expected RT cost or a facilitative effect when both task and modality changed. Both modality-shift and task-switch produced similar RT costs across all ages, and these costs appeared to be additive. Thus, our results suggest some form of inter-trial MSE effect on task-associated processes. However, this inter-trial MSE effect is unlikely to be bound to the imperative elements of the tasks, since modality transition did not interact with response repetition. It is well-known that response repetition is facilitative only when the task repeats, but not when the task changes (Cooper, 2009; Kray & Lindenberger, 2000; Meiran, 1996, 2000, 2005; Rogers & Monsell, 1995), since the facilitative effect depends on task-stimulus-response primes. No such constraint was observed with modality transition, as response repetition was equally facilitative regardless of whether the modality changed or not. This indicates that the modality-associated representation that underlies MSE is unlikely to be an important constituent of the task set. In sum, our behavioural result indicates a role of modality-associated representations on the overall information processes, but the

modality-associated representations are not likely to be significant components in the overall representation of a largely amodal task set.

Thus far, our behavioural results have helped inform the possible relations between different levels of representations within a task-set. Our computational models provide a platform for testing how different information processes give rise to behavioural variations observed in the task set. In the next sections, I will highlight the main findings in the computational models of the bimodal CMTS study.

9.4 Main mechanisms that affect the task performance of the computational models

Flexible behaviours should be investigated by understanding the processes that operate within each task-specific environment. In order to quantify the effects of the control mechanisms and of information interference, information processes within a task context need to be specified beyond the descriptive level. Our computational models consisted of accumulator systems in which evidence was collected from two main processing pathways—one going from task attribute to response outputs, and another going from stimulus to response outputs. There were also temporary priming connections that changed from trial to trial. The models provided a framework for understanding our empirical results in the bimodal CMTS study. The modelling results revealed that task performance was dependent on goal activation, and on the level of carry-over facilitation and interference. These two mechanisms are discussed further below.

9.4.1 Goal activation

Our model results strongly support the idea that top-down control plays an important role in determining overall performance. Adults and 6-year-olds were more accurate overall than 4-year-olds because they had greater top-down control required to activate a task goal *prior* to settling for a response. In adults, the relevant/ irrelevant task goals are likely to be strongly activated/ inhibited during the preparation window. As long as the task goal was sufficiently activated, adults were much better at withstanding other task-based interference factors such as primes and reactive task retrieval. In addition, as long as adults employed a sufficiently high level of top-down control throughout the experiment, then whether they modulated their top-down control according to each trial type had little impact on their performance.

In 6-year-olds, the relevant/irrelevant task goals were likely to be moderately activated/inhibited during the preparation window. Six-year-olds were highly accurate on repetition trials, indicating a sufficient level of top-down control to maintain goal representation against decay. However, in the face of strong interference and/or reactive retrieval on switch trials, they were more likely to make errors on switch trials than adults. In other words, 6-year-olds were not as prepared for the upcoming task as adults, and their goal representations were more vulnerable to task-based interferences.

In contrast to the control exhibited in 6-year-olds and adults, 4-year-olds were likely to show limited top-down control. In the Young networks in our models, the Top signal on repetition trials was only marginally above the bias (see, for example Model 3C, Chapter 7, in which Top=3, bias=-2.5), yet the accuracy on repetition trials remained relatively high (approx. 80%). Thus, it is likely that many of the correct answers on repetition trials were facilitated by

other reactive processes, such as reactive task activation and priming facilitations, and were not the result of a preparatory effect. However, these facilitations were relatively absent on switch trials (other than the occasional reactive task activation when the trial contained a target). Thus, to respond correctly on switch trials, additional top-down control was necessary. Our modelling results suggest that many 4-year-olds did appear to understand the benefit of a greater level of control on switch trial during the preparation window, although they might only be able to do this reactively in response to the additional task cue present on switch trials. Consequently, the poorer performance on the repetition trials in many 4-year-olds may be to do with their inability to sustain sufficient top-down control across trials, when additional encouragements such as change signals are lacking.

In sum, strong top-down control is likely to result in a strong goal representation prior to settling for a response. A strong goal representation can minimise the detrimental effect of subsequent information interference. Although 6-year-olds were able to represent task goals proactively across the duration of the experiment, due to the immature top-down control, their goal representations are still not strong enough to withstand the multiple interferences that occur on switch trial. In comparison, despite a lack of top-down control, 4-year-olds were relatively accurate on repetition trials. Their accuracy on repetition trials may not be due to a strong goal representation, but may arise because of other reactive processes that facilitate responses on repetition trials after the stimulus onset. Despite this lack of overall control, when encouraged by an additional change signal on switch trial, 4-year-olds could reactively modulate their top-down control in response to the environmental changes. Thus, our model results support the role of

endogenous control in goal activation and maintenance during the preparation window, as well as highlighting the role of age in how children modulate their control either proactively or reactively.

9.4.2 Carry-over effects

Although goal activation during the preparation window is the most important factor predicting performance (irrespective of trial types), some features of the switch trials make them more demanding and thus more likely to result in worse performance than on repetition trials. In our models, carry-over effects arose from three main sources—(i) the residual activation/inhibition of the TA units from the n-1 trials, (ii) the PS2TA primes, and (iii) the PS2RO primes. On task repetition trials, these carry-over effects were almost always facilitative, since the activated components in the n-1 trial were still task-relevant on the repetition trials. As a consequence, these resulted in a bootstrapping effect that reinforced the goal representations on successive repetition trials. On switch trials, however, these carry-over effects caused interference since the previously task-relevant components now become task-irrelevant. In this case, the primes might activate the wrong task attribute or the wrong response set.

Although residual activation/inhibition of the TA units and the different types of primes all caused some forms of interference on switch trials, these effects operated at different stages of processing. The residual activation/inhibition are at play at the early stage of processing, particularly during the preparation window. On switch trials, younger networks needed a longer preparation window to overcome the residual TA activations due to their

smaller top-down control. Thus, children are likely to experience a longer effect of carry-over TA interference on switch trials than adults.

In contrast, priming effects came about after the stimulus onset. In our models, the primes were continuous fixed effects until a response was made. Thus, the priming effects were sensitive to the overall speed of response settling. Old networks (adults), were quicker at gathering evidence to generate a response, consequently limiting the impact of the interfering primes. Young networks (children), exhibited larger priming effects because of the relatively slow settling speed due to global network characteristics such as generally smaller connection weights. Unlike the time-limiting effect of residual TA activation, which theoretically can be overcome with a larger preparation window or with a larger Top signal, age differences in priming effect are likely to be resistant to experimental manipulations. In sum, our models suggest that children will experience greater and longer carry-over effects than adult.

9.5 Capturing individual differences with computational models

Although the core factors of goal maintenance and carry-over effects could largely account for the observed developmental differences in the overall performance, our model results also revealed why younger children displayed a greater range of performance variations than adults.

Our model results showed that younger networks were particularly susceptible to certain factors not associated with task preparation or task-based interferences, such as individual differences in self-reminders. Once the preparation was over, without any additional Top signal (i.e. update probability at 0%), the activation of task attribute units started to decay (i.e. the activations

were squashed) with each cycle. As Young and Middle networks were inherently slower than Old networks, due to smaller connection weights, they were also more likely to go through more cycles of decay. The decay of task attribute unit was further compounded by not being fully prepared in the first place because of lower top-down control. Thus, any individual difference in the likelihood of using a remedial tactic following the preparation window, such as using self-reminders, could have a great impact on young children's performance, despite having similar top-down control between individuals.

The probability of remedial self-reminders occurring affected both accuracy and RT on all trial types in the mixed condition in Young networks, but only accuracy on switch trials in Middle networks. In contrast, no effects of self-reminders were found in Old networks. In other words, additional verbal self-reminders can be particularly beneficial to 4-year-olds, and to a lesser extent 6-year-olds. Although our behavioural experiments did not tap directly into verbal reminders or inner speech, we did observe the use of verbal tactic with many 4-year-olds, and occasionally with some 6-year-olds. Thus, children who understood the utility of self-reminders might have achieved higher accuracy than those who did not. In sum, our model results suggested that 4-year-olds were likely to exhibit a greater range of individual difference in both RT and accuracy, than either 6-year-olds and adults, and that 6-year-olds were more likely to exhibit a greater range of individual difference on switch accuracy than adults.

9.6 External task structure and internal task representation

Simply defining a task externally does not necessarily mean that the participants will form an internal representation of the task set consistent with

the external task instructions. In the pure condition, our model results showed that the task could be approached both with or without a goal representation. However, accuracy was likely to be lower without a goal representation, as there was a greater chance that other unspecified distractions would influence the response outputs. In the pure condition, because of a lack of task selection demand, some participants may approach the task simply using S-R rules. Indeed, according to our modelling results, younger children with slower S-R translation would make more errors as a result of distractors or noise (i.e. Intrinsic signals) than adults, whose stronger and faster information processes naturally shielded them from the effects of such noise.

In contrast, the use of active goal representations was more likely in the mixed condition. This is because activating appropriate task goals was an inherent requirement in this condition. . Thus, rather than an *inability* to form appropriate task structures, as Zelazo suggested (Zelazo, 2006; Zelazo, Frye, & Rapus, 1996; Zelazo et al., 2003), young children might simply be less likely to actively form appropriate task structures spontaneously and will only do so if the task encourages them to do so.

Taken together, active goal setting is likely to be sensitive to the perceived need and benefits of setting goals. Thus, to ensure mixing costs reflect the intended differences associated with multiple task sets (e.g. differences in goal activations and/or interference between task sets), it is necessary to ensure that all participants actively form a supramodal task goal in the baseline pure condition. One possible procedure for ensuring this may be to incorporate catch trials in the pure condition.

9.7 Understanding modality shift effects with computational models

Our empirical results in bimodal CMTS show a greater MSE to auditory targets and a nonsignificant smaller MSE to visual targets in the *pure* condition. Two different models—a priming model that was based on asymmetric modality-response pathways, and an MA model that was based on cross-modal carry-over effects with additional modality attribute representations, provided plausible explanations of how the MSE asymmetry might be achieved in the pure condition. Our results showed that the MA model was better at capturing the observed data.

In the priming model, the asymmetric MSE was due to pathway asymmetries. There was a stronger pathway from visual inputs to manual response, and a weaker pathway from the auditory inputs to manual responses. This was intended to reflect a better visual modality-response compatibility. The strength of stimulus-response primes depended on the level of activation of the percept-stimulus unit. Specifically, it was assumed that a longer exposure to the stimulus (due to slower response time) would result in a stronger prime. This did indeed result in an asymmetric MSE, as there was stronger priming facilitation from the slower responses to auditory stimulus, and a weaker priming facilitation from the faster responses to the visual stimulus. Thus, neither priming model involved any additional modality-specific representations other than the asymmetric modality-response compatibilities inherent in the experimental design.

While the asymmetric modality-response pathways could produce asymmetric MSEs through stimulus-response primes, this priming account was not compatible with several empirical observations. Firstly, MSE was only

significant in the presence of auditory targets, but not visual targets, whereas the priming effect was significant in the presence of targets in either modality in the model. Secondly, the priming account was also incompatible with the observation in the unimodal CMTS experiment. In that experiment, we found that modality transition did not interact with response transition. Thus a modality-associated representation is unlikely to be an imperative element of the task-set. The same dissociation between task and modality may also be true in bimodal CMTS. In sum, our empirical results in both the bimodal CMTS and unimodal CMTS, strongly suggested that MSE is more than just a stimulus-response priming effect.

Our MA model offered a more parsimonious account of MSE asymmetry as arising through carry-over effects from additional modality-associated representations. The MA units implemented an n-1 memory mechanism that allowed inter-trial interactions. Our results with the pure networks suggested that asymmetric MSE might be driven by the difference in repetition facilitation that occurs between the stronger and weaker modalities. The facilitative effect from modality repetition is likely to be more evident when the initial strength of the input is weak, as compared to when the input is already strong.

In our models, auditory processing was weaker than visual processing on two levels—a weaker auditory-response pathway that corresponds to the weaker auditory-manual compatibility, and a weaker activation of auditory stimulus. With regards to stimulus activation, we do not know whether the weaker activation of the auditory stimulus corresponds to visual dominance (since all trials contained bimodal stimuli) through cross-modal distraction, or, to the additional need for temporal integration of auditory inputs. However, for whichever reason, auditory stimuli were likely to be weakly activated compared

to the visual stimuli, leaving scope for repetition facilitation. In sum, our MA model was better at capturing the observed behavioural data, particularly in regards to the significant MSE to auditory target, and non-significant MSE to visual targets in the pure condition.

We also observed that the MSE could change with an additional inhibitory modulator from the phonological engagement unit (PE), which represented inner speech or verbal task rehearsal. In the mixed networks, we observed that MSE to auditory targets could be reduced to a non-significant level if this additional PE unit, interacted with the modality-associated units. Specifically, this PE unit mildly inhibited the auditory MA unit and indirectly reduced the facilitation of modality repetition to auditory targets. Our MA model in the mixed networks failed to increase MSE to visual targets. It is therefore possible that there are other mechanisms that interacted with visual processing in the mixed condition.

Overall our results support the general observations that, although MSE is often observable, the direction of asymmetry and the overall size of MSE (significantly greater than zero or not) are changeable under different task contexts. This changeability of MSE makes it differentiable from task-switch costs and stimulus-response priming effects, which were relatively constant across different task contexts.

9.8 Other mechanisms not incorporated in the models

Although our models incorporated multiple levels of representation and information processes, many other mechanisms were not investigated. In this section, I will outline some further mechanisms (not implemented in the models) that may also be at play in our behavioural studies.

9.8.1 Representational conflicts and inhibitory mechanisms

Behavioural research generally does not differentiate between interference and conflicts explicitly; the two terms are often used interchangeably. As the task-switching paradigm involves overlapping task sets, information interference is a natural result of the experimental design. However, these interferences do not necessarily result in representational conflicts. A conflict refers to a situation where more than one representation at the same processing level is positively activated. Thus, although interference often results in some perturbations that may in turn result in RT changes, there is no conflict as long as the competing representations remain inhibited. Although not explicitly stated in our modelling results sections, errors were almost always due to conflicts, whereas RT costs were due to interference with or without conflict.

Since conflicts are particularly detrimental to accuracy, an effective system is likely to have a mechanism to monitor the level of activation/inhibition status of the competing task goals and responses. Younger children may be less sensitive to the status of activation/ inhibition between the competing task goals than adults. This conflict monitoring system may explain the higher order effect such as n-2 repetition cost observed in task-switching studies (Mayr, 2001; Mayr & Keele, 2000; Schuch & Koch, 2003). The n-2 repetition cost refers to the RT cost when switching back to a task that was previously switched away from (e.g. ABA), compared to switching to a new task that was not recently encountered (e.g. CBA). Building upon Gilbert and Shallice's task-switching model, Sexton and Cooper (2017) developed a model that incorporates a layer of processing units that record task conflicts. When the two task attributes are positively activated, the system creates a memory trace of this co-activation conflict and modulates the activation of the task attribute units in the following

trial through inhibitory mechanism. However, this inhibitory mechanism was not involve in active selection as all previously co-activated units received inhibitory inputs from the conflict monitoring units. That is, the inhibitory inputs from the conflict monitoring are *indiscriminate* to what the current task is. For example, in both ABA and ABB sequences, if A and B task attributes were previously co-activated, regardless of whether the final trial in the triplet was A or B, either task attribute would receive inhibitory inputs from the conflict monitoring unit. Thus, the inhibition is non-selective to only the interfering task attribute (e.g. either only B or only A), and therefore may be dissimilar to endogenous control mechanism like top-down control. The role of these inhibitory inputs is not to 'deactivate' the task attributes to such an extent that they become inhibited (i.e. below zero), since it would be nonsensical as both task-relevant and irrelevant representations are involved. Instead, these inhibitory inputs had a universal 'slowing effect' on response settling.

It is not clear if the conflict monitoring system constitutes part of the inhibitory control mechanism. Inhibitory control is generally measured with the ability to suppress motor outputs; but in the context of task-switching, it is often also used to explain various RT slowing such as negative priming, switch cost, and n-2 repetition cost. Research on inhibition phenomena often cannot agree on whether a dedicated inhibitory control module is needed, as other selection processes associated with task demands are often sufficient to account for various RT slowing and stopping failures (Hampshire, 2015; Pritchard & Neumann, 2009; Sharp et al., 2010; Tipper, Jordan, & Weaver, 1999; Tipper, 2001). Since our models did not include an inhibitory mechanism other than the non-selective 'dumb' lateral inhibitory connections which facilitate overall response settling, our models also questions the need for selective 'smart'

inhibitory control in cognitive tasks. Instead, it suggests that different inhibition phenomena, at least in the context of task-switching, simply reflect heterogeneous selection processes aided by additional non-selective modulators such as lateral inhibition and the conflict monitoring system.

9.8.2 Speed-accuracy mechanisms

In our models, the response threshold was critical to whether the network had sufficient opportunity to gather information from the associated information pathways. If the response threshold was set too low, the network would be more likely to make errors since one of the competing response output units may reach the threshold before the network had a chance to rectify the course of response settling. A higher response threshold generally is accompanied with an increase in accuracy. A legitimate question, therefore, is whether children were overall less accurate due to a lower response threshold, suggesting that the errors they made were due to speed-accuracy trade-off (SAT) commonly observed in speeded tasks.

The decision-making in our models follows a principle of 'integrating' different information from the associated pathways, and 'firing' when the activation of a response output exceeds the threshold. In an accumulator-based model, a response is more likely to be accurate if there is a 'safe distance' between the baseline activity and the response threshold. If this distance between baseline activity and threshold is less than ideal, responses are likely to be quicker but more error-prone as there may not be enough time to sample correct information (Fig. 9.1). This shortened distance may be caused by raised overall baseline activity in the network or a lowered response threshold, causing the SAT phenomenon. Although the underlying neurophysiology corresponding

to either baseline activity or response threshold may be different, the effects were the same mathematically speaking (Bogacz et al., 2010).

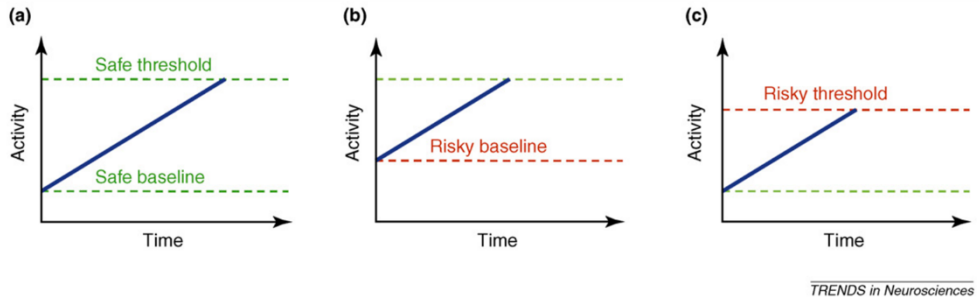

Figure 9.1. Schematic illustration of how speed-accuracy trade-off (SAT) occurs in an accumulator, with processing time shown on x-axis and unit activation shown on y-axis. (a) A safe distance between baseline activity and response threshold enhances accuracy but results in longer RT; (b) a risky elevated baseline activity or a (c) risky lowered response threshold shortens RT but increases the likelihood of SAT-based errors. Figure is borrowed from Bogacz et al. (2010).

Thus, it is possible that young children made more errors in our experiments not (just) because of the weak goal representations and information interference, but of a lower-than-ideal response threshold, resulting in a tendency to respond before an optimal level of information was collected.

In Model 1 (Chapter 5), where there was little information interference and no decay function, younger networks were overall more accurate than older networks. This reflects an advantage of having a smaller baseline activity relative to the response threshold due to weaker connections. This advantage of being 'slow' disappeared in Model 3 (Chapter 7), when the task attribute units were allowed to decay and when there were additional interferences in the networks (e.g. primes and reactive task retrieval). However, the accuracy of

younger networks was again improved in Model 4 (models for MSE effects, Chapter 9) when the response threshold was raised for strategic purposes, effectively widening the distance between baseline activity and response threshold.

It follows that our models cannot rule out the possibility that children made more errors because of the SAT. If this is the case, it would support the idea that children make errors due to failures to prevent prepotent responses (e.g. Davidson et al., 2006; Kirkham & Diamond, 2003; Wright & Diamond, 2014), rather than the failure to maintain task goals. Although in this case a response is prepotent not because of a lack of inhibitory control, but because of a low response threshold. Despite this possibility, information interference and weak goal representation remain central to our account of why young children perform worse than adults because these task-associated factors are the reasons for why a younger network would require a much larger response threshold in the first place.

In sum, how young children and adults maintain the balance between speed and accuracy by either changing the response threshold and/or baseline activation, is clearly critical to the understanding of developmental differences in flexible behaviours. Future studies are needed to determine the speed-response mechanism in young children, and what the underlying neural basis are in both children and adults.

9.8.3 Task strategies

Our models pointed to some speculations about the use of different task strategies in different age groups, such as a proactive strategy in which the participants employed the same level of high top-down control across all trial

types, in order to optimise speed and accuracy, or, a reactive strategy in which the participants only employed a greater level of top-down control when detecting a need to do so. However, our models did not specify any mechanism that would account for how different networks would modulate top-down control. One such mechanism may be the conflict monitoring system that was mentioned earlier. However other harder to specify mechanisms, such as idiosyncratic characteristics of each participant (e.g. some people may try harder than the others), may also exist.

There are also theoretical issues with how task-strategy can be defined. For example, in our model, we defined a task-strategy as 'proactive' when the same top-down control was used throughout the experiment, regardless of whether the participant made a greater number of errors on switch trials, such as in the case of 6-year-olds in the bimodal CMTS. However, other researchers might see 6-year-olds as 'not proactive enough' or being 'reactive' on switch trials. This begs the question whether "proactivity" and "reactivity" should refer to the subjective effort within a specific developmental level of competence, and would perhaps be more closely associated to neurophysiological responses, or, whether it should rest on a more objective definition in which suboptimal performance (relative to some absolute level of competence) would be labelled as 'reactive' and 'not proactive'.

9.8.4 Learning mechanisms

Other than the temporary connections that allow priming effects, all of our networks have manually fixed connections. The differences in connection weights may correspond to both experience-dependent learning and experience-independent changes such as pruning and myelination. These

weights embody global characteristics of a specific age group. Indeed, weight changes in a connectionist model have traditionally been used to simulate learning and/or development, with stronger weights representing a more mature or experienced network (Elman et al., 1996; Leech, Mareschal, & Cooper, 2007; Munakata & McClelland, 2003; Sirois & Shultz, 1998). For example, connectionist models that aimed to explore developmental differences often involve a 'training' stage in which the network 'learns' by modifying weights between different levels of processing units, and a 'testing' phase to see how the network perform after learning (see Mareschal, 2010; Mareschal & Thomas, 2007, for a review). The network's performance could therefore be traced back to the differences in how connection weight changed across simulated development. Thus, despite the fact that the weights in our current models were hand-set, the underlying assumption that the fundamental between-group differences are underpinned by the global differences the connection weights, is the same as in other learning-based connectionist models.

Because our experiments were concerned with the existing ability to shift attention, either between tasks or between modalities, learning was not considered to be an important dimension during the experiments. However, it remains possible that learning could take place within the experiment, especially for young children who might need a greater number of exemplars to establish the associations between different task elements. Future modelling works should therefore incorporate some form of learning other than temporary priming effects within networks of different ages.

9.9 Model limitations

The greatest limitations of the models are two-folds—the connection weights of different age groups were manually fixed, and the top-down control was simplified into a single input. On the first issue of the connection weights, network ages were constructed in a slightly arbitrary manner. Furthermore, all networks were constructed with a strict criterion that they should be able to achieve 100% accuracy at zero noise and zero decay.

This is because the models were extremely sensitive to the precise balance among all information pathways. If one pathway was much stronger than the other, the network would always make the same deterministically defined errors. The reason for adopting the 100% accuracy criterion was based on the assumption that young children made errors not just because of their inability to construct tasks appropriately, but also because of other modulatory factors such as top-down control and interferences. This remains a fundamental assumption of the models that is yet to be tested empirically.

We know that adults were likely to construct the task sets appropriately since they achieved near-ceiling accuracy. We can also be relatively confident that 6-year-olds were also likely to do since their accuracy on repetition trials was high. However, we could not say for certain that 4-year-olds did construct the task set appropriately and did not make deterministic errors in the experiments. Therefore, alternative explanations such as deterministic errors (i.e. errors caused by constructing the task set inappropriately, such that the child might always respond to a specific stimulus in the same way regardless of the task goal) could potentially account for the behavioural results in (some) 4-year-olds.

The second issue (regarding Top signals) is more critical because this parameter is central to our account of the observed developmental differences in behaviour. Although it is plausible that children had weaker top-down control, how this weaker top-down control is translated into a smaller Top signal within our models remains unclear. There may be a whole host of mechanisms that modulate inputs from the higher level of processing into task attribute units. For example, the greater Top input could equate with greater connection weights from the higher processing level to the task attribute level in adults than in children. Thus, Top 'inputs' are equivalent to connection weights feeding in activation from additional processing layer. However, what these processing layers are, and what mechanisms may modulate top-down control are not specified in the current models. Thus, our models can be improved by specifying more precisely how the connection weights are derived and what other higher order processing layers exist.

Another limitation is that, although our models provide an account of what mechanisms may underlie the changes in performance on each trial type, they might not fit behavioural measures perfectly. For example, task strategies by trial type (i.e. modulation of Top signal) in our models were based on the assumptions that the participant of a specific age was more or less likely to adopt a specific task strategy (e.g. reactive task strategy in adults). However, it is entirely possible that there was a wide range of individual differences within each age group. These individual differences will have a direct effect on the size of the switch costs observed. To perfectly capture the behavioural results at both between-subject and within-subject levels, requires a clear specification of how each participant at each age group approached the task—an undertaking not possible with the sample size and the experimental design in our studies.

Instead of striving for a perfect fit to the behavioural data perfectly on all levels, our models focused on mechanistic (process level) explanations of behaviour rather than closeness of fit to the observed behavioural data. The consequence of focusing on mechanistic level of explanation is that making precise prediction can be challenging, given that a small parameter change often result in complex behavioural changes. Adding additional processing layers and mechanisms to the models is likely to further increase the difficulty of fitting model results to behavioural studies with multiple measures.

9.10 Future directions

In this thesis, I have presented how the task-switching paradigm can be used to explore cognitive flexibility in young children. Despite some evidence that 4-year-olds could reconfigure task goals according to environmental changes, our model results also suggest that 4-year-olds were overall poor at maintaining task goals (Freier et al., 2017). Our results are in agreement with the Crone et al.'s (2006) finding that the ability to switch task goals emerges earlier than the ability to maintain a task goal. In their experiment, the participants (8 to 9 years old, 11 to 12 years old, 14 to 15 years old, and young adults) were asked to sort some stimuli based on feedbacks. This experimental paradigm was similar to the Wisconson Card Sorting Task but with child-friendly materials. They found that adult-level of distractor error was reached much later than adult-level of perseverative error, indicating that children were overall poorer in maintaining task goal consistently.

Thus, cognitive flexibility should not only refer to the ability to initiate a representational and behavioural change, but also the skill in consistent performance. Our studies and models indicate that complex effects such as

mixing costs and switch costs were not appropriate indices of cognitive flexibility in young children, as low accuracy on baseline trials and individual differences in remedial tactics (e.g. self-reminders) may obscure these between-condition effects. In adults, although a very large top-down control theoretically can eliminate RT switch cost in our models, the performance gains on RT are relatively small. In fact, a person might be considered more 'savvy' if the task goal is neither too weakly nor too strongly activated—if the goal activation is too weak, interferences would be relatively impactful during response settling; conversely, if the goal activation is too strong, there would be a longer process in deactivating the task goal on switch trials. A 'savvy' participant is likely to conserve attentional resource to prevent fatigue, given that the experiment requires sustained attention. Since RT and accuracy on either pure, repetition or switch trials depends on multiple factors, from the internal representation of the task structure, developmental constraints on top-down control, and task strategies, to remedial tactics of self-reminders, between-condition mixing and switch costs do not necessarily directly index developmental differences. Instead, understanding how mixing costs and switch costs arise is useful in uncovering what underlying information processes are involved on different trial types, but these two costs do not necessarily reveal whether a participant has more or less cognitive control.

So how do we move forward from the results in the current thesis. Although conventional complex between-condition measures themselves may not be particularly useful for understanding behaviours in either children or adults, taking a holistic account of accuracy, RT, and carry-over effects such as different types of primes, are helpful for understanding why young children are particularly susceptible to involuntary effects such as priming

facilitation/interferences and other forms of reactive memory retrievals. For example, children might experience greater interference because of their slower response speed. Thus, it follows that if young children can be trained to be more efficient at translating a stimulus into responses, and translating task goals into selection of response sets, the effect of involuntary interference/ facilitation may be reduced. However, our models also suggest that, even if their overall RT improves with practice, if young children's top-down control is indeed constrained by development, they are still likely to make many more errors than older children or adults.

The Task switching paradigm can also be useful for understanding individual differences in children's tendency to modulate top-down control (i.e. proactive vs. reactive strategies), and in other remedial tactics such as verbal self-reminders. We found greater individual differences in 4-year-olds, which matched our model results. If the use of verbal self-reminders was indeed a tactic particularly useful to young children, individual differences among children may narrow on tasks that cannot be represented in verbal form, or when the articulatory systems are suppressed. Future studies should aim to elucidate whether the individual differences observed in young children can be captured by differences in cognitive ability (such as working memory), differences in complementary tactics, and/or the efficiency in translating task elements into responses.

With regards to modality-associated effects, our behavioural results and models show that concurrent or carry-over modality-associated effects are likely to come from lower-level processes. Future studies should investigate which mechanism underlies the weaker activation to auditory stimuli. For example, if the weaker activation was due to concurrent cross-modal interferences, such as

that caused by modality dominance, the asymmetric MSE in the pure condition should disappear with unimodal stimuli. The modality-associated representations appeared to be independent to task-associated representations, although modality shift effects could be influenced by cognitive processes that are also engaged in modality-associated pathways, such as verbal or inner speech. Modality-associated effects are often composite effects of complex interactions, as asymmetric processes exist on many different levels—from potentially developmentally-dependent modality dominances, task-dependent modality advantages underpinned by modality-task/modality-response compatibilities, different temporal integration of perceptual inputs, to other factors such as spatial attention. These different asymmetric processes potentially make understanding developmental differences in modality-associated effects particularly challenging, given that the different processes might interact with one another. Thus, developmental differences in modality-associated processes might first need to be explored in a relatively simple environment before moving on to more complex task condition, in order to tease apart different levels of information asymmetries.

In sum, future studies should aim to answer questions such as why young children still perform less well than older children and adults, despite exhibiting a reasonable ability in the overall task?; What causes the larger individual differences in performance in younger children?; and What are the developmental differences in asymmetric modality-associated pathways, from concurrent cross-modal interferences to modality-task compatibilities?; and whether the developmental differences in asymmetric modality-associated pathways are due to the maturation of multisensory system, or to the effect of learning.

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Appendix A. Glossary of terminology

Terminology	Definitions
A2A	A trial with two consecutive auditory targets. It is a modality-repetition trial
A2V	A trial with a visual target that was preceded by a trial with an auditory target. It is a modality-shift trial
Auditory dominance	See modality dominance
Backward inhibition	See n-2 repetition cost
Bi-selection	Choosing between two inputs from target sets
Bias	A defined negative value in the model that determines how much net input is required to positively update a processing unit
Bimodal CMTS:	Cross-modal task-switching behavioural experiment with bimodal stimuli
BV/BA	Visual and auditory percept-stimulus units in the bird stimulus set
BY/BN	Yes and No RO units in the Bird response set
Carry-over effect	Any effect that arises from the previous trial(s)
Cross-modal	Between modalities
Cycle	A unit of time in the computational models. Activation states are updated at every cycle
DCCS	Dimensional Card Change Sorting task

Terminology	Definitions
DV/DA	Visual (DV) and auditory (DA) percept-stimulus units in the Dog stimulus set
DY/DN	Yes and No RO units in the Dog response set
IA model	Interactive activation model
Intrinsic signal	A signal that is sent to the response output units (RO), without the mediation of a higher level representation such as a TA unit. It represents the effects of task-unrelated noise
Irate	The learning rate of associative connections between two processing units. This parameter is used to model priming connections
MA	Modality attribute unit: a unit that represents modality-associated representations that can result in cross-modal interactions
MA_{AUD}	Auditory modality attribute unit
MA_{VIS}	Visual modality attribute unit
Mixing costs	Differences between mixed task (network) and pure task (network) performance
Modality dominance	An attentional bias to inputs from the dominant modality when encountering multisensory information
Modality-shifting	Shifting between modalities

Terminology	Definitions
MR	Modality-repetition trial: when the target modality in the n-1 trial is the same as the current target modality. See also TR/TS
MS	Modality-shift trial: when the target modality in the n-1 trial is different from the current target modality. See also TR/TS
MSE	Modality shift effect in reaction time, calculated as the difference between the reaction time in the modality shift trial and modality repetition trial
Multi-tasking	Managing multiple tasks in a given context
n-2 repetition cost	A performance cost in returning to a task that had previously been switched away from
Negative priming	Reaction time cost in attending to information that was previously ignored
Neutral set	The stimulus input that is not associated to any task
Non-paradoxical asymmetry	When an attentional shift cost is larger when switching to the more difficult condition than to the easier condition
Nonresponse	An absence of button-press in our experiments. See also response
Paradoxical asymmetry	When an attentional shift cost is larger when switching to the easy condition than to the difficult condition

Terminology	Definitions
PE unit	A unit indicating phonological engagement (PE) such as when engaged in self-reminders
Perceptual preparation window	A time window to allow PS units to be updated before response settling begins
Population approach	Understanding global behaviour by constructing a population sample with individual differences
Preparation window	A time window that allows the participants/network subjects to retrieve/activate the task goal (task attribute) before the stimulus onset
Primed response	A button-press on a trial that contains a prime. In our experiments, a prime is stimulus-led in pure and repetition trials, and response-led in switch trials (see also *stimulus-led primed trial*, *response-led primed trial* and *unprimed response*)
Priming compound	A priming compound is formed when multiple representations become associated due to an episodic event, which can result in priming effect on the following trial(s)
Priming cost	RT cost from the excitatory priming effect from the previous trial(s), most commonly observed in switch trials.
Priming facilitation:	RT facilitation from the excitatory priming effect, most commonly observed in pure and repetition trials.

Terminology	Definitions
Proactive control	Sustained cognitive control in anticipation of the need to respond
Proactive strategy	When the network (participant) employs a strong Top signal on both repetition and switch trials. The definition of a 'strong' signal is dependent on (network) age
Processing speed	The time it takes in translating mental representations into measureable responses
Production system	Rule-based (i.e. symbolic) computational model
PS input:	An external input to the unit that represents a perceptual stimulus
PS unit:	A unit that represents a perceptual stimulus.
PS_{AUD}	Auditory percept stimulus
PS_{VIS}	Visual percept stimulus
PS-RO	Fixed feedforward connections from percept-stimulus (PS) units to response-output (RO) units
PS-TA	Fixed feedforward connections from percept-stimulus (PS) units to the corresponding task attribute (TA) units
PS2RO	Temporary priming connections from percept-stimulus (PS) units to response-output (RO) units
PS2TA	Temporary priming connections from percept-stimulus (PS) units to task attribute units (TA)

Terminology	Definitions
Reactive control	Transient cognitive control in response to an environmental change
Repeated-response	A response (button-press) preceded by another response (button-press)
Response	A button-press in our experiments
Response-led primed trial	A trial preceded by an n-1 trial that also results in a button-press.
RO unit:	A unit that represents a response output
RP	Response prime: a form of priming that is defined by the occurrence of a response repetition.
RR	Response repetition: a button-press preceded by a button-press.
Single-response	A response (button-press) preceded by a nonresponse (withholding button-press)
Squash	A fixed parameter that decreases the activation of a processing unit by a certain percentage
Step	The rate of activation update of a processing unit
Stimulus-led primed trial	A trial preceded by an n-1 trial that contains a stimulus from the same target set and of the same modality as the stimulus in the current trial
Subadditive effect	A processing cost that is less than the expected combined cost of modality-shift and task-switch when these two costs are simply added together.

Terminology	Definitions
Switch costs	Performance differences between switch trials and repetition trials in the mixed task condition (network)
TA unit:	Task attribute unit. This is conceptually equivalent to a task goal representation
Target set	The stimulus input that is associated to one of the two tasks
Task set	A task set comprises multiple components that are necessary for achieving a task goal
Task set inertia	Collective interferences formed from the previous trial or trials
Task-switching	Switching between tasks, which result in switch cost
Task-relevant	Relevant to the current task goal
Top	An endogenous input to the task goal representation in the model. It is conceptually equivalent to top-down control
Top-down signal:	See Top
Top-down update	Updating goal representations such as the TA unit through top-down signal
TR	Task-repetition trials. Trials in which the task is the same as in the n-1 trial. For example a MRTR is a modality-repetition task-repetition trial (see also MS/MR)

Terminology	Definitions
TS	Task-switching trials. Trials in which the task is different from the n-1 trial For example a MSTS is a modality-shift task-switch trial (see also MS/MR)
Uni-selection	Choosing between one input from the target set and one input from the neutral set
Unimodal CMTS:	Cross-modal task-switching behavioural experiment with unimodal stimuli
Unimodal TS:	Task-switching behavioural experiment with unimodal stimuli
Unprimed response	A correct button-press in trials in which the n-1 trial does not prime the current event in any way
Update frequency	This refers to the probability of sending a top-down input to the TA unit. This parameter defines inter-network differences (i.e. each network subject has its own update frequency)
V2A	A trial with an auditory target that was preceded by a visual target. It is a modality-shift trial
V2V	A trial with two consecutive visual targets. It is a modality-repetition trial
Visual dominance	See modality dominance
WM	Working memory